Estimation of supply and demand in the Spanish energy market

Eric Serra, Roberto Ivo, Celma de Oliveira Ribeiro

DEPARTAMENTO DE PRODUÇÃO
UNIVERSIDADE DE SÃO PAULO
CAMPUS DE BUTANTÃ
Avenida Vital Brasil, 1490 - Butantã - São Paulo
BRASIL

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1. INTRODUCTION

In recent years, electricity has been gaining a greater presence in the lives of all citizens. The International Energy Agency considers that the future will become increasingly electric by the possibility of consuming energy that will be generated progressively by clean technologies **[1].** All this makes the price of electricity becoming a very important element for the society, both for domestic users, who pursue an economical and transparent energy, as well as for the companies and industries, that want to maintain their competitiveness in an open and globalized environment.

In mid-nineties started in Europe the liberalization of the electrical sector, which means that from that moment the energy delivered to the net is negotiated in a market. This liberalization, which arrived in Spain in 1997 **[2],** brought several changes to the energy sector with the aim of bringing to citizens the benefits of a free market, in terms of a better price and a better service.

Nowadays, there exist different ways in which the electricity can be negotiated in the Spanish energy market, from bilateral contracts, where energy is negotiated directly between the agents, to organized markets, where products are negotiated in long term (OMIP) or with a few hours in advance (OMIE) **[3].** This studio is focused in the study of the day-ahead market, since it is considered the most important one. That is because is the market with more volume of negotiation and the one that has more influence in the final price of the electricity.

Forecasting techniques have been gaining increasing importance in recent times, since they allow to predict the behavior of certain parameters in the future and have many areas of application within the scientific world. Among the current best-known techniques are Auto-Regressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), Adaptive Wavelet Neural Network (AWNN), and many other hybrid models **[4]**.

The main objective in this article is to estimate supply and demand in the Spanish energy market using ARMA/ARIMA models. First, the history and the dynamic of the Spanish energy market will be studied. Then, the operation of the day-ahead market will be analyzed more accurately, focusing on the offers made by market agents, that is to say, the energy auction, and the procedure to determine the final price of electricity. Afterwards, a short introduction to time series and prediction models will be made. Next, an adapted database containing the offers of market agents will be constructed with the help of market operator website and, finally, the software *R-project* will allow to predict and forecast the supply and the demand of electricity in the Spanish energy market.

2. SPANISH ENERGY MARKET

2.1 Introduction to the electrical system

Electricity demand is seasonal in the short and long term with high degrees of randomness. Our consumption not only changes throughout the day, also throughout the week, depending on whether it is a working day or a holiday, and also throughout the year, depending on the season in which we are.

Electricity is not stored, at least simply and in large quantity. Consequently, the oversizing of the electrical system is a technical requirement for its stability. Therefore, it is important to highlight the complexity of the operation of an electrical system, in which what is consumed at any moment is being generated at the same instant. Thus, the installed capacity of the system has to be permanently superior to the highest point of demand reasonably probable, taking into account the probability of failure, the maintenance coincidences or the randomness and seasonality of certain generation systems such as hydraulics, wind power, etcetera.

The electrical system is organized into four different activities: generation, transport, distribution and consume **[5].** The generation is carried out by the producers, those agents in charge of generating electricity from a given energy resource. To date, there are many alternatives with very varied characteristics.

Red Eléctrica de España (REE) is responsible for the transport **[6].** Their function is to transport the electricity generated in the power plants. This concept is reserved to long distances, which are saved through high-tension lines. Once near the place of consumption, the distribution is responsible for bringing each consumer this electricity in medium and low voltage lines.

2.1.1 Stable legal framework (MLE)

From 1988 to 1997, the Spanish electricity sector was regulated by the stable legal framework. Considering electricity as a basic element for the development of the country and the welfare of society, there was an intervention by the state, assuming the responsibility to organize and plan the system **[5].**

The stability of this framework was based on assuring to the electrical companies acceptable benefits and the recovery of their inversions in the long term, as well as in establishing in a transparent way tariffs to the consumers in conditions of minimum cost.

The agents that constituted the stable legal framework were the four discussed above. In the case of generators, they were paid the recognized standard cost, which varied depending on the type of generation and power plant. The transport network was nationalized by creating Red

Eléctrica de España, with the idea that the most efficient form of transport is the monopoly. In the distribution, the companies that already existed in each zone of the Spanish territory were maintained, and they were paid a recognized cost for that service. The final consumers paid the full rate, which was obtained by dividing the total costs of the system by the expected demand for that year.

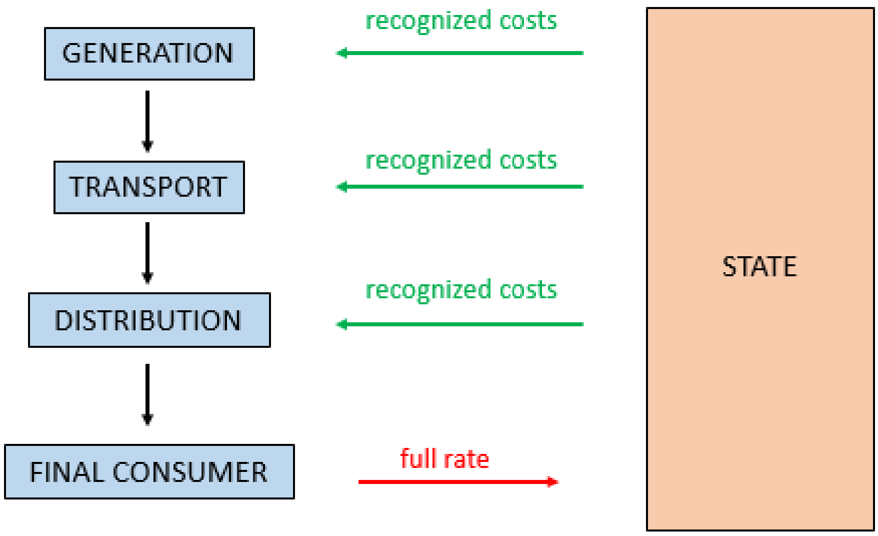

Figure 1. Scheme of the main actors of the stable legal framework. Black arrows indicate flows of electricity. Red and green arrows indicate monetary flows.

In this way, the electrical system could be understood as a closed chain in which the consumers assumed the total costs of the system at prices regulated by the Administration, prices that in turn assured to the electrical companies the recovery of their investments and covered other costs previously recognized by the State.

2.1.2 The Iberian electricity market

From 1997 onwards, a gradual liberalization of the electricity market takes place, reaching what is now known as the Iberian market for electricity. With this change, the intention was that decisions that with the old framework corresponded to the State now would be managed by free market mechanisms. In summary, the regularization of the state continues in the transportation and distribution, while the generation and the commercialization is liberalized.

In this manner, in the generation a company can decide at its own risk to install a plant that posteriorly will be remunerated by market mechanisms. In the commercialization, the consumers choose a marketer in the retail market, and these marketers in turn buy the electricity to the generators in the wholesale market **[5].**

The main difference now is that the cost of kWh includes two components that are obtained separately. On the one hand, there is the regulated component, expected to cover the costs of the system, that is to say, transport and distribution costs, as well as other incentives that still are responsibility of the state such as incentives for availability, premiums to the special regime, etc. The state collects from the marketers the part corresponding to the regulated component and then divides it between REE and the distributors. On the other hand, there is the market component that is obtained by free competition mechanisms in the wholesale market, to which the marketers and the direct consumers such as big industries come to negotiate.

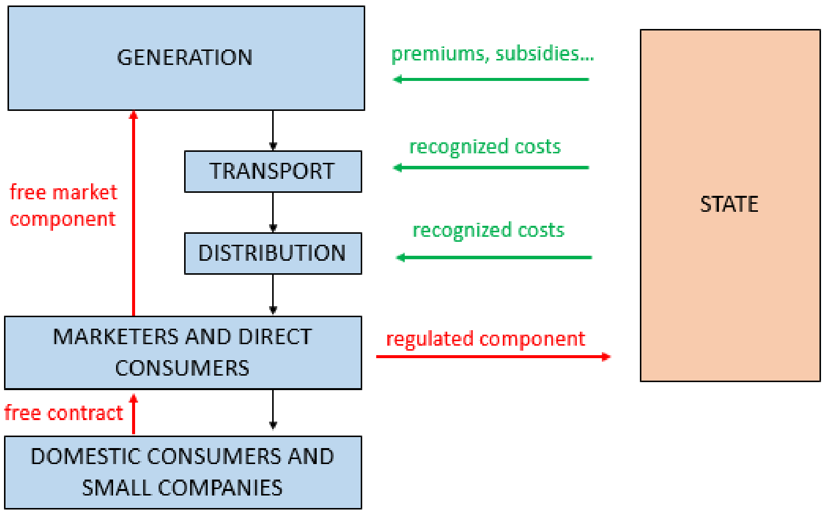

Figure 2. Scheme of the main actors of the liberalized market. Black arrows indicate flows of electricity. Red and green arrows indicate monetary flows.

2.2 Characteristics of the Spanish energy market

The demand of electrical energy in Spain was 265.3 TWh for the year 2016 **[7],** suffering a slightly increment (0.8%) respect the previous year. On the other hand, the national generation decreased 1.9% in comparison to 2015, affecting mainly the coal sector. In relation to international exchanges, importations exceeded exportations in 7313 GWh, a fact that did not occurred since 2003.

BALANCE ELÉCTRICO ANUAL (1)	Sistema peninsular		Sistemas no peninsulares		Total nacional	
	GWh	% 16/15	GWh	% 16/15	GWh	% 16/15
Hidráulica	39.049	25,1	4	-1,7	39.053	25,1
Nuclear	55.546	1,4	-	-	55.546	1,4
Carbón	34.740	-31,8	2.298	23,2	37.038	-29,8
Fuel/gas (2)	-	-	6.748	3,9	6.748	3,9
Ciclo combinado (3)	26.186	3,6	3.601	-10,5	29.787	1,7
Hidroeólica	-	-	19	117,3	19	117,3
Eólica	48.507	1,7	420	4,6	48.927	1,7
Solar fotovoltaica	7.570	-3,5	409	2,6	7.979	-3,2
Solar térmica	5.102	0,3	-	-	5.102	0,3
Otras renovables (4)	3.440	8,4	11	4,8	3.451	8,4
Cogeneración	25.843	1,7	35	10,2	25.878	1,7
Residuos	3.049	2,1	275	-11,6	3.324	0,8
Generación	**249.031**	**-2,1**	**13.819**	**2,0**	**262.850**	**-1,9**
Consumos en bombeo	-4.846	7,2	-	-	-4.846	7,2
Enlace Península-Baleares (5)	-1.232	-7,8	1.232	-7,8	0	-
Saldo intercambios internacionales (6)	7.313	-	-	-	7.313	-
Demanda (b.c.)	**250.266**	**0,8**	**15.050**	**1,1**	**265.317**	**0,8**

Table 1. Electrical balance in Spain for the year 2016.

As observed in Table 1, nuclear energy is still the main source of national generation, followed by wind and hydraulic energy. It is important to note that in comparison to 2015, the coal sector has lost importance, since its production descended in 29.8%, whereas hydraulic energy is the source that has evolved the more. It is interesting to mention the entrance of a new renewable energy in the balance, the hydro wind energy.

To December 31th, 2016 the installed power in Spain was 105308 MW **[7]**, decreasing 0.9% respect the previous year motivated by the closure of several coal centrals that together reached 932.2 MW. The rest of technologies have not suffered any variation, except solar photovoltaic, which increased 0.3%.

POTENCIA ELÉCTRICA INSTALADA A 31 DE DICIEMBRE	Sistema peninsular		Sistemas no peninsulares		Total nacional	
	MW	% 16/15	MW	% 16/15	MW	% 16/15
Hidráulica	20.353	0,0	1	0,0	20.354	0,0
Nuclear	7.573	0,0	-	-	7.573	0,0
Carbón	9.536	-8,9	468	0,0	10.004	-8,5
Fuel/gas	0	-	2.490	0,0	2.490	0,0
Ciclo combinado	24.948	0,0	1.722	0,0	26.670	0,0
Hidroeólica	-	-	11	0,0	11	0,0
Eólica	22.864	0,0	156	0,0	23.020	0,0
Solar fotovoltaica	4.425	0,3	244	0,3	4.669	0,3
Solar térmica	2.300	0,0	-	-	2.300	0,0
Otras renovables (1)	743	0,0	5	0,0	748	0,0
Cogeneración	6.670	0,0	44	0,0	6.714	0,0
Residuos	677	0,0	77	0,0	754	0,0
Total	**100.088**	**-0,9**	**5.220**	**0,0**	**105.308**	**-0,9**

Table 2. Installed electrical power in Spain at the end of 2016.

The development of the transport net experimented in 2016 a new impulse with the incorporation of 674 km of circuit and 600 MVA of transformation capacity, that improved reliability, the degree of mesh, the interconnection between the islands and permitted the evacuation of a major quantity of renewable energy.

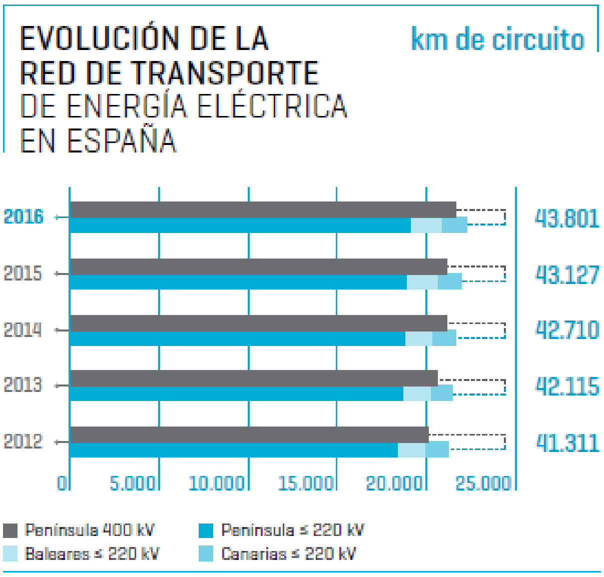

Table 3. Evolution of the electrical energy transport net in Spain.

2.3 Different markets

This section describes the mechanisms by which producers and consumers agree on a price and the amount of energy to be exchanged, thus generating the free market component of the price of electricity outlined in Figure 2.

The products traded in the different markets are extremely varied, including sales of energy delivered during all hours of a quarter closed with half a year in advance (futures market) **[8]** to transactions for energy delivered at a specific time, closed with a few hours notice (daily and intraday markets).

The agents involved in these markets are known as market units, and they are mainly distinguished between producers and qualified consumers **[5].** A production unit generally refers to a physical unit such as a gas turbine, so that a coal power plant with three turbines goes to the markets as three independent market units when making offers. Only in special cases of small power plants, such as wind turbines or photovoltaic plants, it is permissible for a unit to encompass several physical units, as for example in a wind farm.

Producers and consumers can agree a certain price for a certain amount of energy by several mechanisms **[5]**:

- Unregulated markets (OTC market): are bilateral contracts in which a producer and a consumer agree a certain amount of energy at a stable price for a given period.
- Iberian electricity market (MIBEL), where come to negotiate Spanish and Portuguese market agents. It is composed of two poles:
  - Portuguese pole (OMIP), responsible for the futures market, where stable long-term contracts are auctioned.
  - Spanish pole (OMIE), responsible for the spot market. They are hourly markets where prices and quantities are decided for each hour of the year.
- Another series of markets managed by REE to organize the last minute adjustments to ensure the instantaneous balance between generation and consumption: complementary services markets, solution of technical restrictions, management of deviations, etc.

2.3.1 OTC market

In the OTC market, trading is done through brokers to ensure confidentiality and anonymity during negotiations. Once an operation is closed, the broker brings together the contract participants to perfect them and to adopt preventive measures related to counterparty risk.

The most common closed transactions in the OTC market are financial products, which is generally a base product with durations of months, quarters, parts of a year and full years. Nevertheless, because of the very nature of the OTC market, it may be possible to close specific operations, physical or financial, depending on the needs of energy market agents.

As for specific data **[9]**, the volume traded on the OTC market during the month of April 2017 stood around 8.9 TWh, 46.5% lower than the previous month (16.6 TWh, traded in March 2017) and 60.5% lower than the volume traded on that market during the same month of the previous year (22.5 TWh, traded in April 2016). In the first four months of 2017, the total traded volume negotiated was 47.1 TWh, 39.1% lower than the volume traded during the same period in 2016 (77.3 TWh).

As a reference to the OTC market liquidity, it is worth mentioning that the volume traded on this market between January and April 2017 (47.1 TWh) represented 56.9% of the peninsular electricity demand in that period (82.7 TWh).

2.3.2 OMIP market

The International Convention related to the constitution of an Iberian Electricity Market between Spain and Portugal, approved in Santiago de Compostela on 1 October 2004, established a new organizational structure whereby the Iberian Market Operator (OMI) became an entity composed of two parent companies or holders (OMIP SGPS and OMEL), with cross-shareholding of 10% **[10]**.

Each of these two companies owns the property of 50% of the capital of two market management companies, OMI- Portuguese Pole (OMIP), which operates the futures market and OMI-Spanish Pole (OMIE), which operates the spot market.

OMIClear was incorporated on 6 April 2004, currently having a share capital of 7500000€, and OMIP and OMIE as sole shareholders (50% each) with which it jointly participates in several functions to support its activities **[11]**. OMIClear serves as a clearinghouse and central counterparty for operations traded on OMIP and also can act as a central counterparty for operations closed in the OTC market.

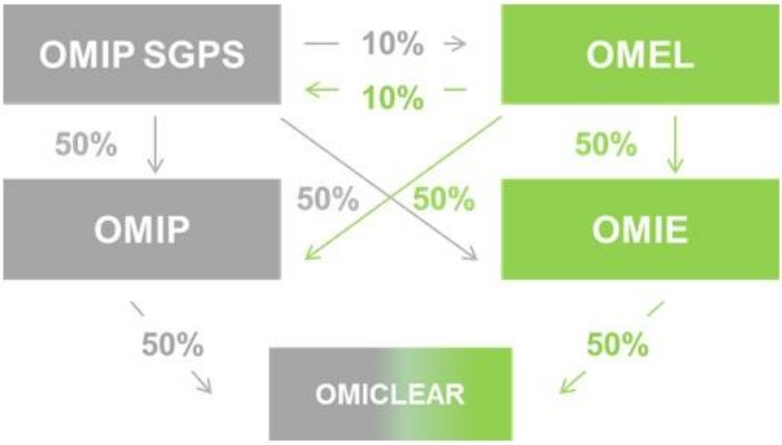

Figure 3. Operation of the Iberian electricity market.

The products traded in OMIP are futures contracts or swaps with different time intervals (days, weeks, months, quarters, years) and time constraints, since there is a difference between the energy trade throughout the day or only in peak hours.

The whole process of negotiation is anonymous, being unknown by the agents behind the operations. In addition, all purchasing and selling orders are public to the participants. To ensure the liquidity of the market, the existence of market makers is promoted. These agents guarantee the existence of a minimum volume for the purchasing and selling operations in return agreed with the profits of the management entity.

2.3.3 OMIE & REE markets

OMIE manages the spot market of electricity in the Iberian Peninsula. As in any market, the electricity market allows the purchase and sale of electricity among market agents at a known, transparent and accessible price.

The price of electricity in Spain is fixed daily every day of the year at 12:00 noon, for each of the 24 hours of the next day, in what is known as day-ahead market **[12]**. The price and volume of energy in a given hour are established by the intersection of supply and demand, following the marginal model adopted by the EU, based on the algorithm approved for all European markets (EUPHEMIA) and currently applied in Spain and Portugal, as well as in many other European countries.

Market agents can attend to the spot market regardless of whether they are in Spain or in Portugal. Their purchasing and selling offers are accepted according to its order of economic merit, until the interconnection between Spain and Portugal is fully occupied. If at a specific hour of the day the capacity of the interconnection is sufficient to allow the flow of electricity traded by the agents, the price of electricity at that hour will be the same for Spain and Portugal. If, on the other hand, at that hour the interconnection is totally occupied, then the price fixing algorithm (EUPHEMIA) is executed separately appearing in this way a price difference between the two countries.

The results of the daily market, based on free contracting between buying and selling agents, represent the most economically efficient solution, but given the characteristics of electricity, it needs to be also physically viable. Therefore, once these results are obtained, they are sent to the system operator (REE) for validation from the point of view of technical feasibility. This process is called management of the technical restrictions of the system and ensures that the results of the market are technically feasible in the transport network. Thereby, daily market results suffer small variations because of technical restrictions analysis conducted by REE, resulting in a viable daily program.

Once the daily market has been completed, and after the process of technical restrictions, the intraday markets are carried out, allowing markets agents to purchase and sell electric energy to adjust their production and consumption to their best forecasts of what they will need in real time **[12]**. There are six auction sessions and its operation is the same as in daily market, where the volume of energy and the price of each hour are determined by the intersection between supply and demand.

Intraday markets allow buyers and sellers to adjust their energetic commitments up to four hours before real time. From that moment, there are other markets managed by the system operator in which the balance of production and consumption is ensured at all times. Complementary services markets aim to ensure that supply is carried out in conditions of safety and reliability at all times, and that imbalances between generation and demand can be solved in real time, maintaining the frequency and power of the network constantly. Deviations management markets are held after each session of the intraday market and serve to resolve imbalances between supply and demand that can be identified a few hours before dispatch. Consists in requesting offers to the generators in the opposite direction to the deviations that are foreseen in the system.

Finally, the energy purchased and sold in the different markets is settled. This settlement and the corresponding invoice are made available to agents on a daily basis. The digital certificate guarantees confidentiality and allows agents to access to their settlement and billing. Collections and payments of each natural week are made on Wednesdays and Thursdays of the following week **[12]**.

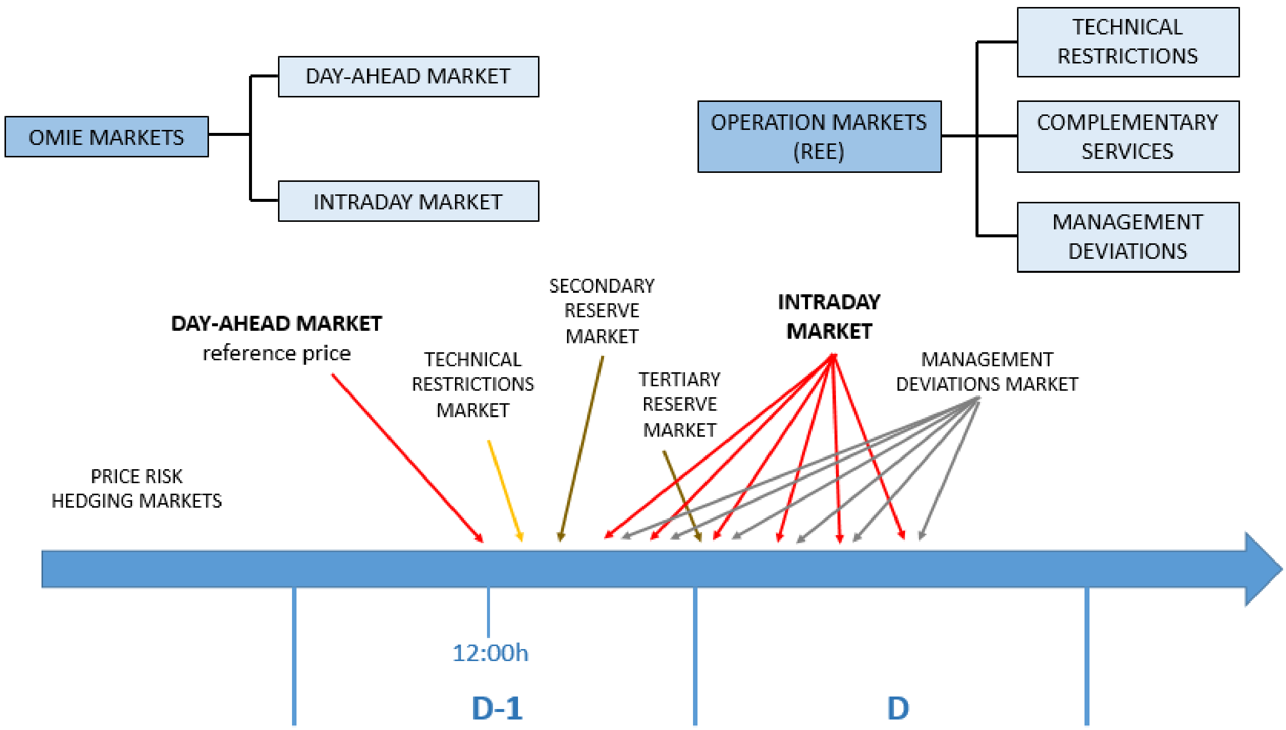

Figure 4. Operation of the spot electricity market and other markets managed by REE.

2.4 Day-ahead market

The day-ahead market is intended to carry out electricity transactions for the next day through offers presentation for the sale and purchase of electric energy by the market agents. All available production units that are not subject to a bilateral contract are required to submit offers in the day-ahead market, except for units less than 50 MW or the ones that were not covered by RD 1538/1987 of Law 54/97 **[13]**. They also could submit sale offers for electricity the non-resident marketing agents authorized to do so.

Sellers and buyers are required to adhere to the operation rules of the electric power production market by subscribing to the corresponding adhesion contract **[14]**. The offers of these market agents will be presented to the market operator, and will be included in a matching process having effects for the daily programming horizon.

2.4.1 Sale and purchase offers

Selling and purchasing offers can be made considering up to a maximum of 25 stretches per hour, in each of which is offered an amount of energy and the price of it. The offer price increases in each stretch in the case of sales, whereas decreases in the case of purchases.

<u>Sale offers</u>

Each generating unit must make before 12 noon its 24 offers for the 24 hours of the following day. An offer consists of a growing curve that relates power stretches and prices to which the generating unit is willing to produce during that particular hour **[5]**. Agents are obliged to offer, by legislation, up to the limit of their capacity of production from the technical point of view, provided it is not committed in bilateral contracts. By contrast, the price is absolutely free, it will depend on each technology.

MW	€/MWh
100	10
+110	30
+130	80

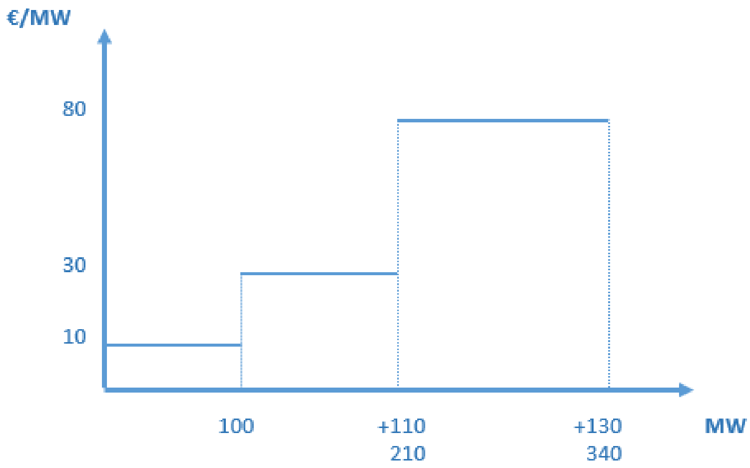

Figure 5. Example of a selling offer with 3 stretches.

The sale bids that generating units submit to the market operator can be simple or incorporate complex conditions **[15]**. Simple bids are sale offers of energy where it is indicated a price and an amount of energy for each period and production unit owned by the sellers. Complex bids are those that meet the requirements governing simple bids, including moreover all, some or one of the four following technical or economic conditions:

- The indivisibility condition allows setting a minimum value of operating power in the first part of each hour. This value can only be divided by applying distribution rules in if the price is different from zero.
- The load gradient allows establishing the maximum difference between the energy of one hour and the energy of the next hour of the production unit, limiting the maximum energy to match to avoid abrupt changes in the production units.
- The minimum income condition allows the realization of bids at every hour, respecting the fact that the production unit does not participate of the matching process of the day if it does not obtain for the whole of its production in the day an income higher than a fixed amount plus a variable remuneration for each matched MWh.
- The programmed shutdown condition allows that if the production unit has been withdrawn from the matching process because it does not meet the requested minimum income condition, it performs a scheduled shutdown in a maximum time of three hours, with the only condition that the energy offered is decreasing in every hour.

<u>Purchase offers</u>

Consumers also have to decide in their purchase offers what amount of energy they want to acquire and at what price they are willing to do so. While a production center has to offer as much as it can to provide sufficient supply, a consumer will offer what he or she considers necessary.

The amount of energy that a consumer has the obligation to consume will have to be demanded at a price high enough to be sure to enter the matching process. At that same time, the consumer might be willing to consume more electricity if the price decreases to a certain value.

Buyers in the electric power production market are the marketers, direct consumers and reference marketers.

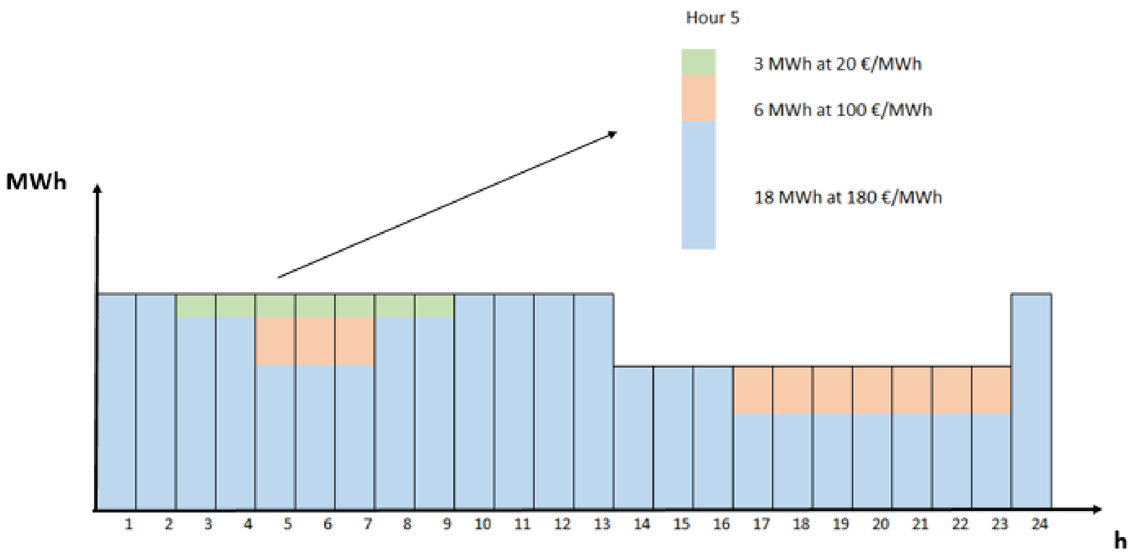

Figure 6. Example of a buying offer.

2.4.2 Offer matching process

The matching process algorithm is Euphemia, used in the vast majority of European daily markets. This algorithm seeks the optimization of the so-called welfare, which corresponds to the sum of the benefits of the purchases offers, plus the benefits of the sales offers, plus the income of congestion.

After 12 noon, the market operator (OMIE) has received all the offers of producers and consumers. What is done then is to generate, for each hour, the aggregate supply and demand curves by ordering, from lowest to highest, all generation offers and from highest to lowest all offers of acquisition. By joining both curves, the intersection point establishes the equilibrium price and the energy to be generated/consumed by each market agent **[5]**. But, as we will see below, this process is not as easy as it seems, as there are several restrictions that come into play, such as the complex conditions or the ability to interconnect with neighboring countries.

Figure 7. Operation of the offer matching process

The market operator will perform the matching of the purchase and sale offers of electricity by the method of simple or complex matching, depending on whether they attend simple or complex offers. In the simple matching method, the marginal price and the volume of electricity accepted for each production unit and for each hourly scheduling period are obtained. The complex matching method obtains the matching result from simple matching method, in which the conditions of indivisibility and load gradient are added. Through an iterative process, different simple matchings are performed until every unit meets the minimum income and the scheduled stop condition.

With this iterative method, the first provisional final solution is obtained by considering an unlimited capacity in international interconnections **[16]**. By another iterative process, it is obtained the first definitive solution that respects the highest international interconnection capacity, considering both offers made to the daily market, as the executions of physical bilateral contracts with external interconnection involvement in the Iberian Market.

The Base Program Operation (PDBF) is the daily program, with an hourly breakdown, of the different production units corresponding to sales and acquisitions of energy in the Spanish peninsular system. This program, published at 14:00, is established by system operators from the schedule resulting of the daily market matching by OMIE and the communication and execution of bilateral contracts. After obtaining PDBF, system operators obtain before 16:00, the Viable Daily Schedule (PDV) by incorporating the amendments necessary for the resolution of technical constraints **[17]**.

2.4.3 Typically, at what prices does each technology offer?

The price at which the producers offer their energy does not represent the variable cost of producing that amount of energy, that is to say, the fuel, starting up the power plant and its operation and maintenance. The offer is made at the opportunity cost of generating that electricity **[5]**, which means that to the previous variable cost must be added the revenues to which the plant relinquishes due to the fact of producing.

For example, for a dam hydro power plant consuming water to produce electricity does not involve any variable cost, but an opportunity cost. This is so because thanks to the dam the generator has the possibility to store the water and consume it in another future time in which the market price is higher. For that reason, reservoir hydro power plants can sell electricity when it suits them and, therefore, offer a high price compared to the rest. However, in a period of heavy rains, if the reservoir is at the limit of its capacity, the opportunity cost will be zero for the energy it can generate with the water it is forced to evacuate, therefore it will make offers at a very low price or even zero, to be sure to enter the matching process.

In the case of coal or gas fired power plants, if the generator can resell the fuel to a third party, then consuming that fuel has an opportunity cost that must be added in the offer to the variable cost for the generation of electricity itself. That is, the opportunity cost is not the price at which the fuel was purchased but the price at which it can be resold.

In the case of a wind farm or a flowing power plant, the fuel is wind or water, which is free, therefore if there is the opportunity to generate in a situation of favorable wind or water stream in the river, the fact failure to do so will not increase the possibility of greater future benefits, since it neither saves on fuel nor can store it for another time. For this reason they will bid at zero price to ensure entry into the matching process.

The rest of generators of special regime, due to the fact that they bring significant advantages for the country, they can take for granted that what they are going to produce is going to be consumed, reason why it can be considered that also make offers at zero price.

Finally, there are the nuclear power plants, which also offer at zero price, but in this case the reason is different. Nuclear power plants have little capacity to vary their level of production over time and are considered base plants, that is, they are all the time producing at their nominal power. Therefore, the offers at zero price seek to ensure entry into the matching process in order to maintain a constant level of production, letting the rest of technologies decide the final price of the auction.

3. METHODOLOGY

3.1 Statistical models (ARMA,ARIMA)

The objective of this section is to introduce the main concepts of time series and ARMA/ARIMA models from a theoretical point of view, without going into detail in the equations nor in the mathematical development, as this study is focused in estimating the demand and supply of the Spanish energy market using the statistical software R-project. Most of the information contained in this section has been compiled from the following books: Applied Econometric Time Series **[18]**, Introduction to Time Series Analysis and Forecasting **[19]**, Análise de Series Temporais **[20]** and Forecasting and Time Series Analysis **[21]**.

For a better understanding of time series, first the concept of stochastic processes must be introduced. A stochastic process is a succession of random variables that evolve over time. The behavior of a stochastic process is non-deterministic, since the subsequent state of the system is determined both by the predictable actions of the process and by random elements.

The possible values that can take the random variables are named states (*X*), so you can have a discrete state space or a continuous state space **[17]**. Otherwise, the time variable (*T*) may be discrete type or continuous type. In the case of discrete time, state changes occur every certain constant period of time (every day, every month, every year, etc.) while in the case of continuous time, state changes could be made at any time.

Thus, the stochastic processes are classified into these four possibilities:

	X continuous	***X discrete***
T continuous	$X_t =$ waiting time of a client arriving at instant t.	$X_t =$ number of people waiting at the bus stop at instant t.
T discrete	$X_t = a$mount of oil to be extracted in month n.	$X_t =$ number of cars sold in Spain in 2016.

Table 4. Summary table with the four possible combinations for stochastic processes.

The data analyzed in this study are the energy offers made by markets agents in the day-ahead market. The time parameter is diary, that is to say, discrete, while the energy and price offered by the agents could take any possible value. Therefore, we have a discrete time and continuous state process.

A time series is a partial realization of a stochastic process and in particular, with discrete time parameter. Therefore, a time series is a collection of observations of well-defined data items obtained through repeated measurements over time. It is important to highlight that data collected irregularly or only once are not time series.

For the analysis of the time series, different methods are used that allow extracting representative information on the underlying relations between the data of the series. Time series allow extrapolating or interpolating the data and thus predict the behavior of the series at unobserved moments, whether in the future (prognostic extrapolation), past (retrograde extrapolation) or intermediate moments (interpolation).

One of the most common uses of temporal data series is their analysis for prediction and forecasting. This is done, for example, with weather data, shares on the stock exchange or demographic data series. Time series forecasting consists basically of estimating the unknown parameters in the appropriate model and using these estimates, projecting the model into the future to obtain a forecast.

In most of the forecasting techniques, errors and observations are assumed to be independent, but this is frequently unwarranted. That is, there are many time series in which successive observations are highly dependent. If this is the case, there are available forecasting techniques which are designed to exploit this dependency and which will generally produce superior results. One of these techniques is Autoregressive Integrated Moving Average (ARIMA) model, which will be used to analyze our time series.

Next, the main concepts of ARIMA model will be explained, as well as the different techniques to verify if the chosen model is adequately adjusted to the time series.

- **AutoRegressive (AR) models**

Autoregressive (AR) models are models in which the value of a variable in one period is related to its values in previous periods.

AR(p) is an autoregressive model with p lags: $y_t = \mu + \sum_{i=1}^{p} \alpha_i * y_{t-i} + \varepsilon_t$ where μ is a constant and α_p is the coefficient for the lagged variable in time t-p.

- **Moving Average (MA) models**

Moving average (MA) models account for the possibility of a relationship between a variable and the residuals from previous periods.

MA(q) is a moving average model with q lags: $y_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \beta_i * \varepsilon_{t-i}$ where β_i is the coefficient for the lagged error term in time t-q.

- **AutoRegressive moving average (ARMA) models**

AutoRegressive moving average (ARMA) models combine both p autoregressive terms and q moving average terms, also called *ARMA(p,q)*.

$$y_t = \mu + \sum_{i=1}^{p} \alpha_i * y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \beta_i * \varepsilon_{t-i} \quad (1)$$

Where,

$$\varepsilon_t \sim N(0,\sigma^2) \rightarrow \text{(white noise)}$$

White noise describes the assumption that each element in a time series is a random draw from a population with zero mean and constant variance. Residuals of and *ARMA(p,q)* model should be white noise.

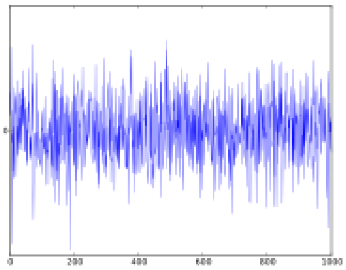

Figure 8. Behavior of the white noise

Another possible model is AutoRegressive Integrated Moving Average (ARIMA) model. When a variable y_t is not stationarity (it will be seen next how to determine this fact), a common solution is to use differenced variable:

$$\Delta y_t = y_t - y_{t-1} \quad (2)$$

This way, *ARIMA(p,d,q)* denotes an ARMA model with p autoregressive lags, q moving average lags, and a difference in the order of d.

The difference between ARMA and ARIMA models resides in the stationary behavior of the time series. An augmented Dicker-Fuller test is performed to detect unit roots **[22]**. Let's assume an AR(1) model to explain the operation of this test.

The model is non-stationary or a unit root is present if $|\alpha| = 1$,

$$\begin{aligned} y_t &= \alpha * y_{t-1} + \varepsilon_t \\ y_t - y_{t-1} &= \alpha * y_{t-1} - y_{t-1} + \varepsilon_t \quad (3) \\ \Delta y_t &= (\alpha - 1) * y_{t-1} + \varepsilon_t = \gamma * y_{t-1} + \varepsilon_t \end{aligned}$$

So, we can estimate the above model and test for the significance of the γ coefficient:

- If the null hypothesis is rejected ($\gamma > 0$), then y_t is stationary. Time series can be modelled by ARMA model.
- If the null hypothesis is not rejected ($\gamma = 0$), then y_t is not stationary. In this case, an integrator term must be added so the time series could be modelled by ARIMA model.

<u>Stationarity and invertibility</u>

ARMA processes must meet two conditions indisputably: stationarity and invertibility.

- **Stationarity**

Modeling an *ARMA(p,q)* process requires stationarity. A stationarity process has a mean and variance that do no change over time and the process does not have trends. The stationarity of a time series can be determined by taking arbitrary "snapshots" of the process at different points in time and observing the general behavior of the time series. If it exhibits "similar" behavior, one can then proceed with the modelling efforts under the assumption of stationarity.

The stationarity of an ARMA process is related to the AR component in the model and can be checked through the roots of the associated polynomial, which is developed from equation:

$$r^p - \alpha_1 * r^{p-1} - \alpha_2 * r^{p-2} - \cdots - \alpha_p = 0 \qquad (4)$$

As mentioned before when explaining the Dicker-Fuller test, if all the roots of the previous equation are less than one in absolute value, then *ARMA (p, q)* is stationary.

- **Invertibility**

It is usual to call a moving average model invertible if it has an equivalent autoregressive representation of infinite order. The importance of the invertibility requirement is that a non-invertible moving average model cannot be used to forecast.

Like in the stationarity condition, the invertibility of an ARMA process is related to the MA component and can be checked through the roots of the associated polynomial, which is developed from equation:

$$r^q - \beta_1 * r^{q-1} - \beta_2 * r^{q-2} - \cdots - \beta_q = 0 \qquad (5)$$

If all the roots of the previous equation are less than one in absolute value, then *ARMA (p, q)* is said to be invertible.

Until now, *ARMA(p,q)* model has been explained but we have not mentioned how to determine the parameters p and q, that is to say, the order of the ARMA model. The procedure to be followed is to test different models and obtain certain factors that will inform the goodness of fit. Akaike information criterion (AIC) and Bayesian Information Criterion (BIC) are two factors that measure the goodness of fit and help to choose the appropriate model **[23]**. The lower AIC and BIC values are, the better the model is adjusted to the time series.

In order to obtain the values of p and q, the correlation between continuous observations can also be analyzed. For that, the functions of simple and partial autocorrelation must be studied.

- **Autocorrelation function (ACF)**

The autocorrelation function (ACF) is defined as the proportion of the auto-covariance of y_t and y_{t-k} to the variance of a dependent variable y_t.

$$ACF(k) = \frac{Cov(\, y_t,\, y_{t-k})}{Var(\, y_t)} \tag{6}$$

Thereby, the autocorrelation function ACF(k) gives the gross correlation between y_t and y_{t-k}.

- **Partial autocorrelation function (PACF)**

Partial autocorrelation function (PACF) is the simple correlation between y_t and y_{t-k} minus the part explained by the intervening lags.

$$PACF(k) = Corr[(y_t - E(y_t | y_{t-1}, \dots, y_{t-k+1})), y_{t-k}] \tag{7}$$

Where $E(y_t | y_{t-1}, \dots, y_{t-k+1})$ is the minimum mean-squared error predictor of y_t by $y_{t-1}, \dots, y_{t-k+1}$.

The tool used in the analysis of these functions is the correlogram. By using this tool, you can get the value of p and q, seeking the last significant coefficient that exceeds the limit. Then you should check if the AR (p) and MA (q) coefficients are significant in the model.

<u>ACF and PACF properties</u>

	AR(p)	**MA(q)**	**ARMA(p,q)**
ACF	Tails off	Cuts off after lag q	Tails off
PACF	Cuts of after lag p	Tails off	Tails off

Table 5. Properties of ACF and PACF in the different time series models.

4. ANALYSIS AND DISCUSSIONS

4.1 Database

All the offers made by the agents in the day-ahead market are published on the website of the market operator (OMIE). These offers are initially anonymous, and after 90 days the authors are revealed. The offers on the website include both offers from Spanish and Portuguese agents. For this studio have been taken all the offers made in the day-ahead market during the year 2016.

The offers, among other data, specify the offering unit, if it is a sale offer or a purchase offer, the amount of energy in MW, the price at which they are willing to sell/purchase in €/MWh, and the time period to which they refer.

Before modeling the data with the software R, it has been necessary to transform and adapt them. In order to facilitate the modeling, the sum of the energy offered by all agents and the average price of all the offers have been taken for each hour of each day, separating between purchasing or selling offers. Finally, all the data referred to the same time period have been put together separately, so for each time period we have the sum of energy and the average price of the successive 366 days of the year 2016.

For example, that would be the sum of energy and the average price offered by the agents during the firsts 10 days of 2016 referred to the first time period, which corresponds from 12:00am to 12:59am, separating between purchasing and selling offers.

Time Period	Purchasing price (€/MWh)	Purchasing energy (MW)	Selling Price (€/MWh)	Selling energy (MW)
1	82,52	33512	45,79	62954,4
1	78,81	34070,8	46	75529,7
1	80,21	35481,4	44,11	69205
1	78,8	35149,1	42,03	77981,5
1	78,25	36701,8	37,84	75451,4
1	78,88	36541,4	37,52	74856,7
1	76,61	36541,6	37,79	77656,1
1	77,75	38634,3	37,11	75423,2
1	83,36	38483,2	36,8	69800,9

Table 6. Database used to in the modeling with software R.

In this way, 24 ARMA/ARIMA models for each and every variable will be determined with the statistical software R-Project **[24]**, one for each hour of the day.

4.2 Results

As mentioned before, an ARIMA model has been made for each variable in each hour of the day. What is sought is to determine if the price and energy offered in the day-ahead market in previous days at a specific time period influence the price and energy offered today at that same period. In addition, it is also intended to determine if it is possible to establish a model that allows making forecasts about how the price and the amount of energy offered for that time period will behave in the future.

Due to the large amount of data and because it is a repeated process, they will be only shown the results obtained for a specific hour, choosing the one that presents a higher energy demand (9:00pm-9:59pm). The results obtained for the rest of the time periods will be shown in the annex. The process of analysis is repeated for the four variables of the system: purchasing price (Pc), purchasing energy (Qc), selling price (Pv) and selling energy (Qv).

Fisrt, the data is plotted to see its general behavior:

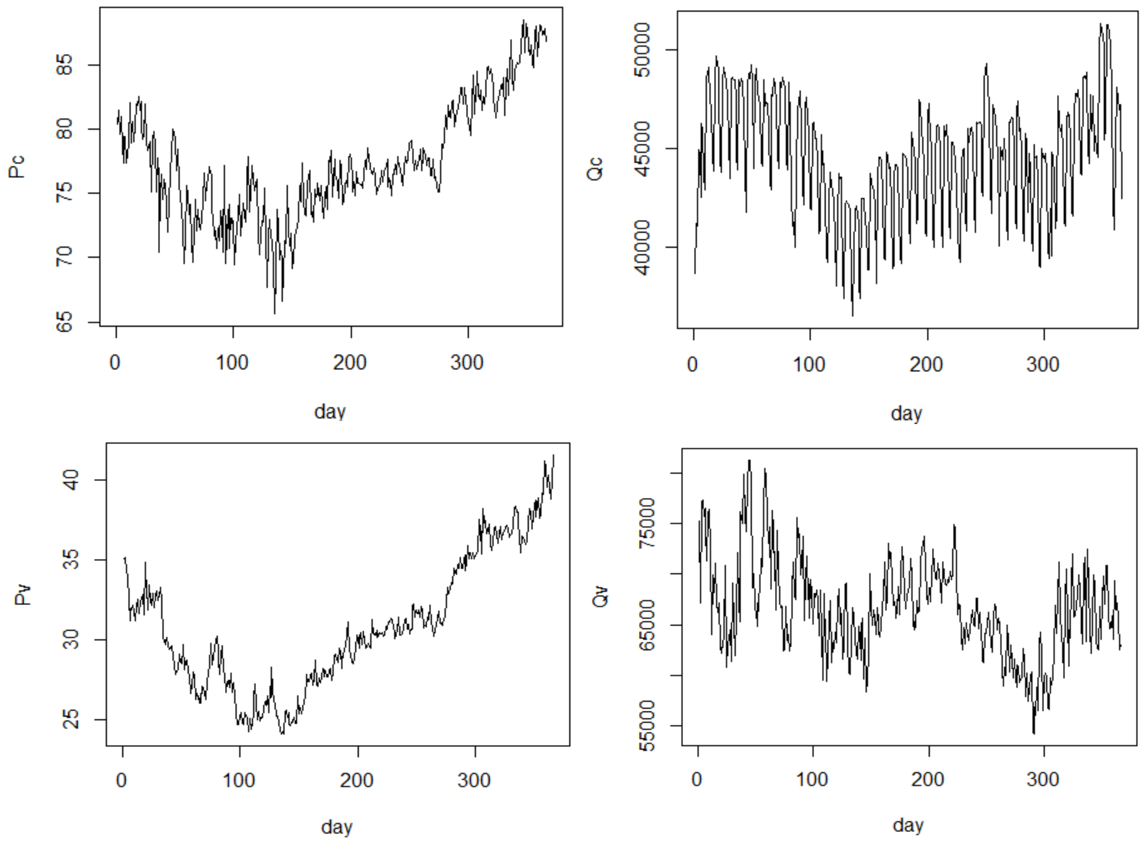

Figure 9. Behavior of the different variables.

As first impression, both purchasing and selling price variables start decreasing and then, suddenly, they begin to increase permanently until the end of the year. On the other hand, the variables refering to the amount of energy seem to show a more random behavior.

Once the data is plotted, the first step is to determine if the variable is stationary or not. In order to determine this, an augmented Dicker-Fuller test is performed. The null hypothesis is the non-stationarity of the variable (*Ho: non-stationarity*), while the alternative hypothesis is the stationarity of the variable (*Ha: stationarity*). If the p-value obtained in the test is close to zero (in this studio we will assume a statistical significance of 5%), the variable is considered stationary. If not, the variable is non-stacionarity and it is needed to add an integrator term and repeat the test with de variable differentiated.

```
data:  Pc
Dickey-Fuller = -2.1678, Lag order = 7, p-value = 0.5061
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.9551, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -2.5126, Lag order = 7, p-value = 0.3606
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.1748, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.6053, Lag order = 7, p-value = 0.7435
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.1986, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.3051, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.1801, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

Figure 10. Augmented Dicker-Fuller test for all the variables of the system.

The p-value obtained for the variables Pc, Qc and Pv is greater than the value 0.05, so the null hypothesis cannot be rejected. In this case it is needed to add an integrator term and repeat the test with the differentiated variable, obtaining stationary results. On the other hand, the variable Qv gives a p-value close to zero, so technically it can be considered stationary and could be modelled by ARMA. Nevertheless, an augmented Dicker-Fuller test with the differentiated variable will also be performed, in order to maintain the same pattern in data analysis and also to demonstrate that using a differentiated variable is always a useful tool to turn a time series into a stationary process.

Next, for each variable the model that better fits the data is calculated, that is to say, the values of p,d,q of the ARIMA model. In order to calculate these parameters, an interative process is made testing different values under the criteria of lowest AIC and BIC, and using ACF and PACF as unit root tests. The tool used in this stuido is the *auto.arima* function from R. For purchasing and selling price as well as for purchasing energy, it has been selected the differentiated variables, while for selling energy it has been used the original variable.

The obtained results are the following:

```
Best model: ARIMA(2,0,2) with non-zero mean
Best model: ARIMA(5,0,1) with non-zero mean
Best model: ARIMA(2,0,2) with non-zero mean
Best model: ARIMA(3,0,1) with non-zero mean
```

Variable	ARIMA model
Diff(Pc)	ARIMA(2,0,2)
Diff(Qc)	ARIMA(5,0,1)
Diff(Pv)	ARIMA(2,0,2)
Qv	ARIMA(3,0,1)

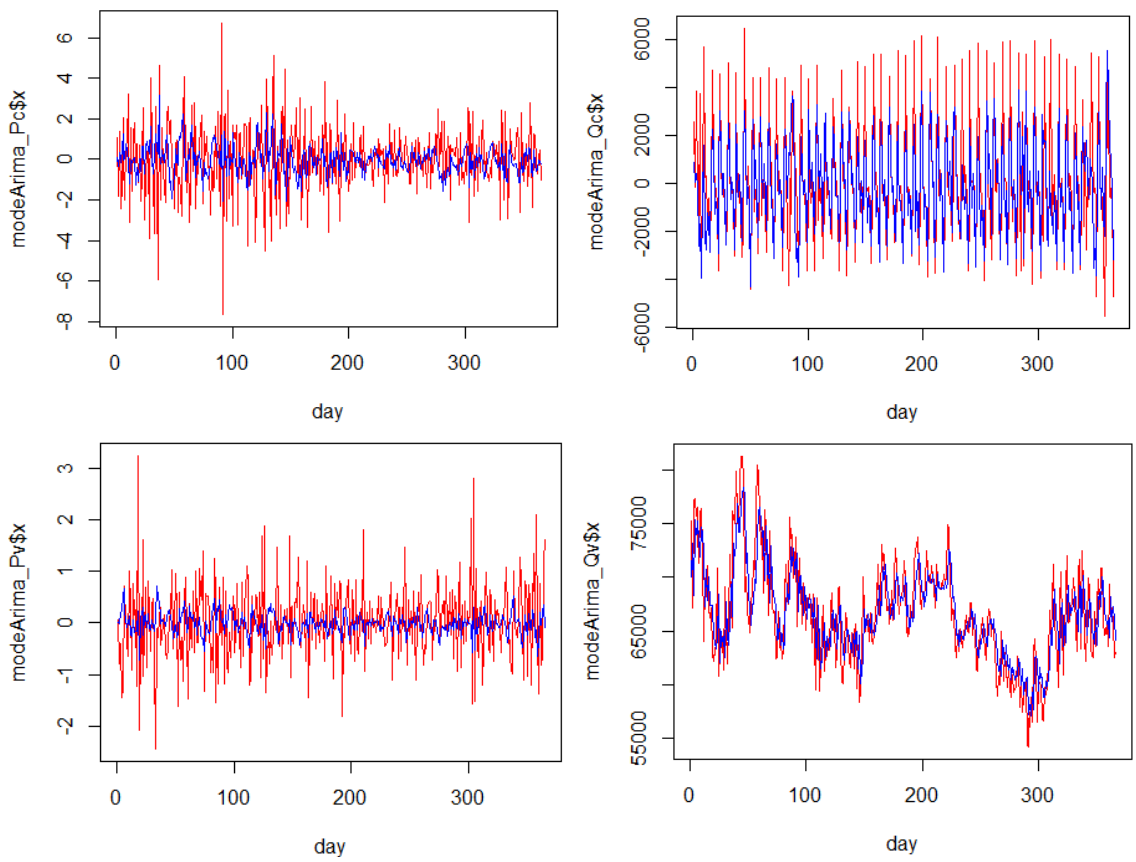

Figure 11. ARIMA models adjusted to each variable.

Red line is the original data, while blue line is the adjusted model. As can be observed in Figure 11, all models fit pretty well the original data, since they are the ones that have provided lower values for AIC and BIC factors.

As mentioned before, one of the main objectives in this studio is to estimate the supply and demand energy that will be offered in the day-ahead market in the nearer future. The software R allows to do that, obtaining the following results for the period beetwen 9.00pm and 9:59pm:

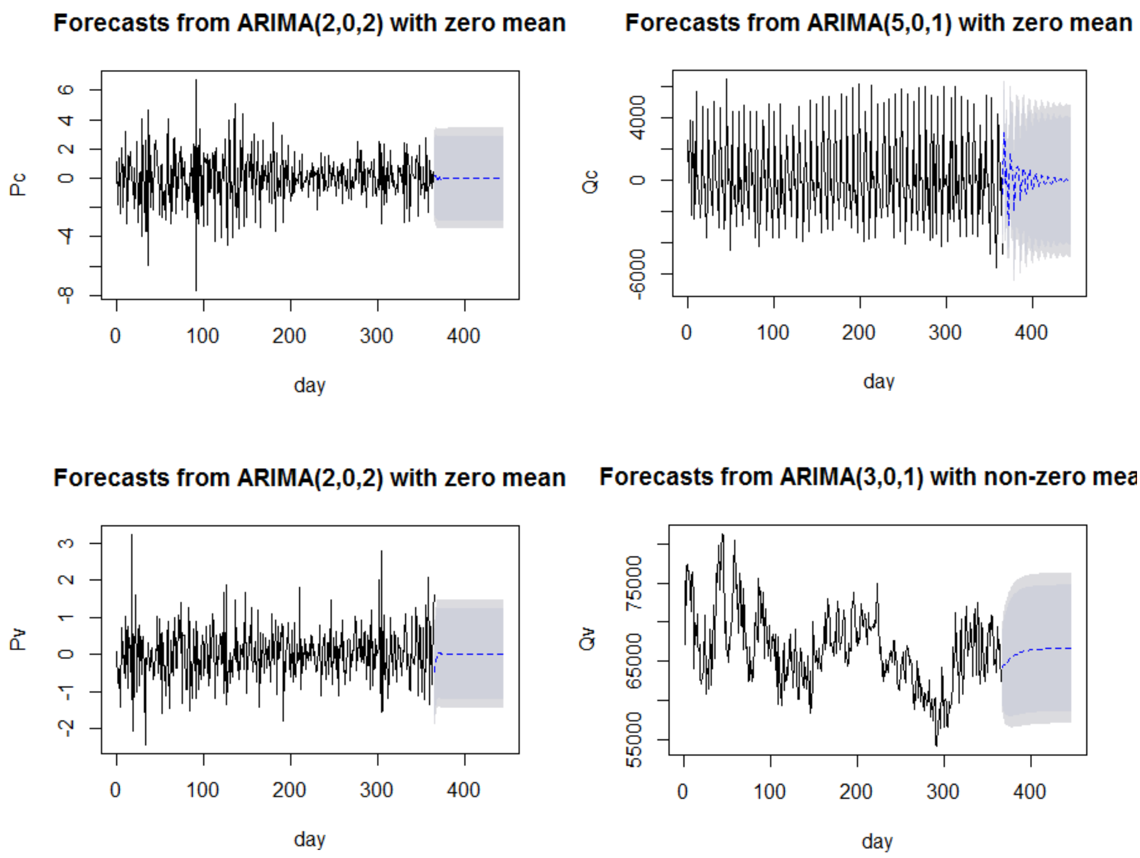

Figure 12. Forecast of price and energy offered by market agents for both purchasing and selling.

In this studio forecasts have been made up to 80 days forward. In all four variables, the data seem to behave in a stationary way, so it could be affirmed that the values in the near future of energy and price offered by market agents in this time period will not significantlly differ from the actual and past values.

Besides the forecasted point, a confidence interval can also be provided, ie, that interval in which it is estimated that the unknown value will be with a certain probability of success. For example, next is showed the confidence interval for the selling energy variable (Qv) both at 90% and at 95% level of confidence, referring to the first 34 days from the last day from which the data were collected:

Selling energy (Qv)		Confidence interval			
Day	Point Forecast	Lo 90	Hi 90	Lo 95	Hi 95
367	64317.32	59462.12	69172.53	58531.99	70102.66
368	64544.61	58793.88	70295.35	57692.19	71397.04
369	64497.22	58468.99	70525.45	57314.15	71680.30
370	64634.50	58322.93	70946.07	57113.80	72155.20
371	64824.56	58219.75	71429.36	56954.45	72694.66
372	64969.85	58129.98	71809.72	56819.64	73120.06
373	65089.82	58065.08	72114.56	56719.33	73460.32
374	65205.67	58026.27	72385.08	56650.88	73760.47
375	65315.99	58005.22	72626.76	56604.67	74027.31
376	65417.33	57995.92	72838.73	56574.18	74260.47
377	65510.41	57995.88	73024.93	56556.30	74464.52
378	65596.60	58003.32	73189.88	56548.65	74644.55
379	65676.47	58016.40	73336.54	56548.93	74804.01
380	65750.35	58033.57	73467.12	56555.24	74945.45
381	65818.66	58053.70	73583.63	56566.14	75071.19
382	65881.86	58075.89	73687.82	56580.48	75183.24
383	65940.32	58099.44	73781.20	56597.34	75283.30
384	65994.40	58123.77	73865.04	56615.96	75372.84
385	66044.43	58148.42	73940.44	56635.76	75453.11
386	66090.71	58173.06	74008.37	56656.24	75525.18
387	66133.53	58197.39	74069.66	56677.04	75590.02
388	66173.13	58221.21	74125.05	56697.84	75648.42
389	66209.77	58244.37	74175.16	56718.41	75701.12
390	66243.66	58266.75	74220.57	56738.58	75748.73
391	66275.01	58288.26	74261.76	56758.21	75791.81
392	66304.01	58308.85	74299.17	56777.19	75830.83
393	66330.84	58328.48	74333.19	56795.44	75866.23
394	66355.65	58347.15	74364.16	56812.94	75898.37
395	66378.61	58364.85	74392.37	56829.63	75927.60
396	66399.85	58381.59	74418.11	56845.51	75954.19
397	66419.50	58397.39	74441.60	56860.57	75978.42
398	66437.67	58412.28	74463.06	56874.82	76000.51
399	66454.48	58426.27	74482.69	56888.28	76020.68
400	66470.03	58439.42	74500.65	56900.97	76039.10

Table 7. Confidence interval of Qv at 90% and at 95% level of confidence.

It is also possible to obtain the model equation. For this purpose, first the intercept and the coefficients of the equation are determined with R, as well as their standard deviation, and then it is determined whether they are statistically significant or not. For this, the value of the coefficient is divided by its standard deviation, and if the result is greater than 1.96 (value to which the *T-student* distribution tends for many degrees of freedom), then the coefficient is accepted as statistically significant and is included in the model equation.

```
Series: diff(Pc)
ARIMA(2,0,2) with zero mean

Coefficients:
          ar1     ar2     ma1      ma2
      -0.5732  0.3145  0.1882  -0.7390
s.e.   0.1029  0.1024  0.0779   0.0795

sigma^2 estimated as 2.553:  log likelihood=-687.24
AIC=1384.49   AICc=1384.65   BIC=1403.99
```

$$y_t = -0.573 * y_{t-1} + 0.315\, y_{t-2} + 0.188 * \varepsilon_{t-1} - 0.739 * \varepsilon_{t-2} \tag{8}$$

```
Series: diff(Qc)
ARIMA(5,0,1) with zero mean

Coefficients:
          ar1      ar2      ar3      ar4      ar5      ma1
      -0.0404  -0.5563  -0.3279  -0.3141  -0.5834  -0.2826
s.e.   0.0515   0.0395   0.0491   0.0396   0.0450   0.0476

sigma^2 estimated as 2624818:  log likelihood=-3214.16
AIC=6442.32   AICc=6442.63   BIC=6469.62
```

$$y_t = -0.556 * y_{t-2} - 0.328 * y_{t-3} - 0.314 * y_{t-4} - 0.583 * y_{t-5} - 0.283 * \varepsilon_{t-1} \tag{9}$$

```
Series: diff(Pv)
ARIMA(2,0,2) with zero mean

Coefficients:
         ar1      ar2      ma1     ma2
      1.2046  -0.3494  -1.4717  0.5715
s.e.  0.2644   0.2043   0.2471  0.2031

sigma^2 estimated as 0.5094:  log likelihood=-392.88
AIC=795.77   AICc=795.94   BIC=815.27
```

$$y_t = 1.205 * y_{t-1} - 1.472 * \varepsilon_{t-1} + 0.572 * \varepsilon_{t-2} \tag{10}$$

```
Series: Qv
ARIMA(3,0,1) with non-zero mean

Coefficients:
         ar1      ar2     ar3      ma1       mean
      0.9976  -0.2609  0.1792  -0.3629  66662.012
s.e.  0.1953   0.1361  0.0664   0.1970   1128.838

sigma^2 estimated as 8712860:  log likelihood=-3441.79
AIC=6895.57   AICc=6895.81   BIC=6918.99
```

$$y_t = 66662.012 + 0.998 * y_{t-1} + 0.179 * y_{t-3} \tag{11}$$

Figure 13. Equation of the model for all the variables of the system.

For reasons already discussed above, this studio only presents the results obtained for the time period between 9:00pm and 9:59pm, but to understand how the day-ahead market works and how their energy and price offers behave, it is needed to analyze all time periods.

In order to do that, and following the order showed before, first an augmented Dicker-Fuller test will be made for all four variables in each time period, to see whether if the variable is stationary or if it is needed to use the differentiated variable to determine the model and the forecasts. The level of significance chosen for this test has been 5%.

The results obtained are the following, where S means Stationarity and N means Non-stationarity:

	Purchasing price (Pc)	Purchasing energy (Qc)	Selling price (Pv)	Selling energy (Qv)
12:00am-12:59am	N	N	N	S
1:00am-1:59am	N	N	N	S
2:00am-2:59am	N	N	N	S
3:00am-3:59am	N	N	N	S
4:00am-4:59am	N	N	N	S
5:00am-5:59am	N	N	N	S
6:00am-6:59am	N	S	N	S
7:00am-7:59am	N	N	N	S
8:00am-8:59am	N	N	N	S
9:00am-9:59am	N	N	N	S
10:00am-10:59am	N	N	N	S
11:00am-11:59am	N	N	N	S
12:00pm-12:59pm	N	N	N	S
1:00pm-1:59pm	N	N	N	S
2:00pm-2:59pm	N	N	N	S
3:00pm-3:59pm	N	N	N	S
4:00pm-4:59pm	N	N	N	S
5:00pm-5:59pm	N	N	N	S
6:00pm-6:59pm	N	N	N	S
7:00pm-7:59pm	N	N	N	S
8:00pm-8:59pm	N	N	N	S
9:00pm-9:59pm	N	N	N	S
10:00pm-10:59pm	N	N	N	S
11:00pm-11:59pm	N	N	N	S

Table 8. Augmented Dicker-Fuller test for all variables in all time periods.

As observed in Table 8, results are quite clear. First of all, the selling energy (Qv) presents a stationary behavior in all time periods, so the original variable can be used to calculate all models and forecasts. On the other hand, the purchasing price (Pc), the purchasing energy (Qc) and the selling price (Pv) present a non-stationary behavior in all time periods, except for variable Qc that in only one specific period shows a stationary result. For these three variables, it will be required to use the differentiated variable to calculate the models and forecasts.

Last, the model that better fits the data will also be calculated for all variables in each time period. The values of p, d and q obtained for each ARIMA model are the following:

	Purchasing price (Pc)	Purchasing energy (Qc)	Selling price (Pv)	Selling energy (Qv)
12:00am-12:59am	ARIMA(1,0,1)	ARIMA(0,0,2)	ARIMA(2,0,2)	ARIMA(1,0,2)
1:00am-1:59am	ARIMA(2,0,1)	ARIMA(3,0,3)	ARIMA(2,0,2)	ARIMA(1,0,2)
2:00am-2:59am	ARIMA(2,0,2)	ARIMA(3,0,3)	ARIMA(2,0,2)	ARIMA(3,0,2)
3:00am-3:59am	ARIMA(2,0,2)	ARIMA(3,0,3)	ARIMA(2,0,2)	ARIMA(3,0,2)
4:00am-4:59am	ARIMA(2,0,1)	ARIMA(3,0,3)	ARIMA(2,0,2)	ARIMA(3,0,2)
5:00am-5:59am	ARIMA(2,0,1)	ARIMA(3,0,3)	ARIMA(2,0,2)	ARIMA(3,0,2)
6:00am-6:59am	ARIMA(1,0,1)	ARIMA(2,0,3)	ARIMA(2,0,2)	ARIMA(3,0,2)
7:00am-7:59am	ARIMA(0,0,2)	ARIMA(2,0,4)	ARIMA(2,0,2)	ARIMA(3,0,2)
8:00am-8:59am	ARIMA(2,0,3)	ARIMA(2,0,4)	ARIMA(1,0,1)	ARIMA(2,0,3)
9:00am-9:59am	ARIMA(0,0,2)	ARIMA(3,0,4)	ARIMA(1,0,1)	ARIMA(3,0,2)
10:00am-10:59am	ARIMA(2,0,4)	ARIMA(4,0,3)	ARIMA(1,0,1)	ARIMA(1,0,2)
11:00am-11:59am	ARIMA(2,0,3)	ARIMA(4,0,3)	ARIMA(2,0,0)	ARIMA(3,0,2)
12:00pm-12:59pm	ARIMA(0,0,2)	ARIMA(4,0,3)	ARIMA(0,0,2)	ARIMA(3,0,2)
1:00pm-1:59pm	ARIMA(2,0,2)	ARIMA(3,0,2)	ARIMA(2,0,0)	ARIMA(3,0,2)
2:00pm-2:59pm	ARIMA(2,0,3)	ARIMA(3,0,2)	ARIMA(0,0,2)	ARIMA(3,0,2)
3:00pm-3:59pm	ARIMA(0,0,2)	ARIMA(4,0,3)	ARIMA(0,0,2)	ARIMA(3,0,2)
4:00pm-4:59pm	ARIMA(0,0,2)	ARIMA(2,0,4)	ARIMA(0,0,2)	ARIMA(3,0,2)
5:00pm-5:59pm	ARIMA(1,0,2)	ARIMA(2,0,4)	ARIMA(2,0,3)	ARIMA(3,0,2)
6:00pm-6:59pm	ARIMA(2,0,2)	ARIMA(4,0,3)	ARIMA(2,0,5)	ARIMA(3,0,2)
7:00pm-7:59pm	ARIMA(2,0,2)	ARIMA(4,0,4)	ARIMA(0,0,2)	ARIMA(3,0,2)
8:00pm-8:59pm	ARIMA(2,0,2)	ARIMA(3,0,2)	ARIMA(0,0,2)	ARIMA(3,0,0)
9:00pm-9:59pm	ARIMA(2,0,2)	ARIMA(5,0,1)	ARIMA(2,0,2)	ARIMA(3,0,1)
10:00pm-10:59pm	ARIMA(1,0,1)	ARIMA(3,0,3)	ARIMA(0,0,2)	ARIMA(3,0,1)
11:00pm-11:59pm	ARIMA(3,0,3)	ARIMA(3,0,3)	ARIMA(2,0,2)	ARIMA(1,0,2)

Table 9. ARIMA models for all variables in all time periods.

First of all, specify that the models in green, stationary, have been made with the original variable, while the models in red, non-stationary, have been made with the variable in the first difference. Analyzing the information in Table 9, we can identify certain patterns that are repeated in the variables. The most repeated model in both purchasing and selling price is ARIMA(2,0,2), which means that the price offers made by market agents in the day-ahead market mostly depend on the offers made yesterday and the day before yesterday, as well as the residual values obtained on those same days.

On the other hand, the purchasing energy is the variable with the highest number of different results, which denotes certain random behavior. However, the results show a certain similarity in the interval of time between the 10:00pm and the 6:00am, which are the periods of less consumption. In the remaining periods, the results have a more random behavior and generally show higher values of p and q.

Finally, the selling energy is the variable that shows more constant results, concretely the model ARIMA(3,0,2). This likeness detected in the models might be due to the fact that the legislation prohibits generators from hiding supply, that is, they are always obliged to bid up to the limit of their technical capacity.

A more detailed analysis of each of the time periods is shown in the annex, attached at the end of this studio. The code used in R is also shown in the annex.

5. CONCLUSIONS

The main objective of this studio has been achieved, since it has been able to estimate approximately the supply and demand in the Spanish day-ahead market. Time series prediction techniques have been correctly applied to the initial database, obtaining this way models, forecasts and equations that allow estimating the evolution of prices and energy both for purchasing and selling offers.

The main technique used in this study is ARIMA process, a technique that, as it can be observed from the obtained results, works quite well but not perfectly due to the volatility of the data being anilyzed. Nevertheless, the operation of the Spanish energy market has been succesfully understood, and this studio has been capable to determine that enery and prices offered by market agents in the past have their particular influence in the energy and prices offered today in the day-ahead market.

Although the main objective has been achieved, this studio has faced several limitations, mainly of time. It would be interesting to analyze in the future the supply and demand of energy using a broader database, ie, not only comprising one year but several years. It would also be interesting to study how the different generation technologies influence the evolution of price and energy offers. In short, energy is a fundamental good in our society and will have more and more protagonism in the following years. So this article definitely deals with a very interesting subject and has great potential for improvement.

6. REFERENCES

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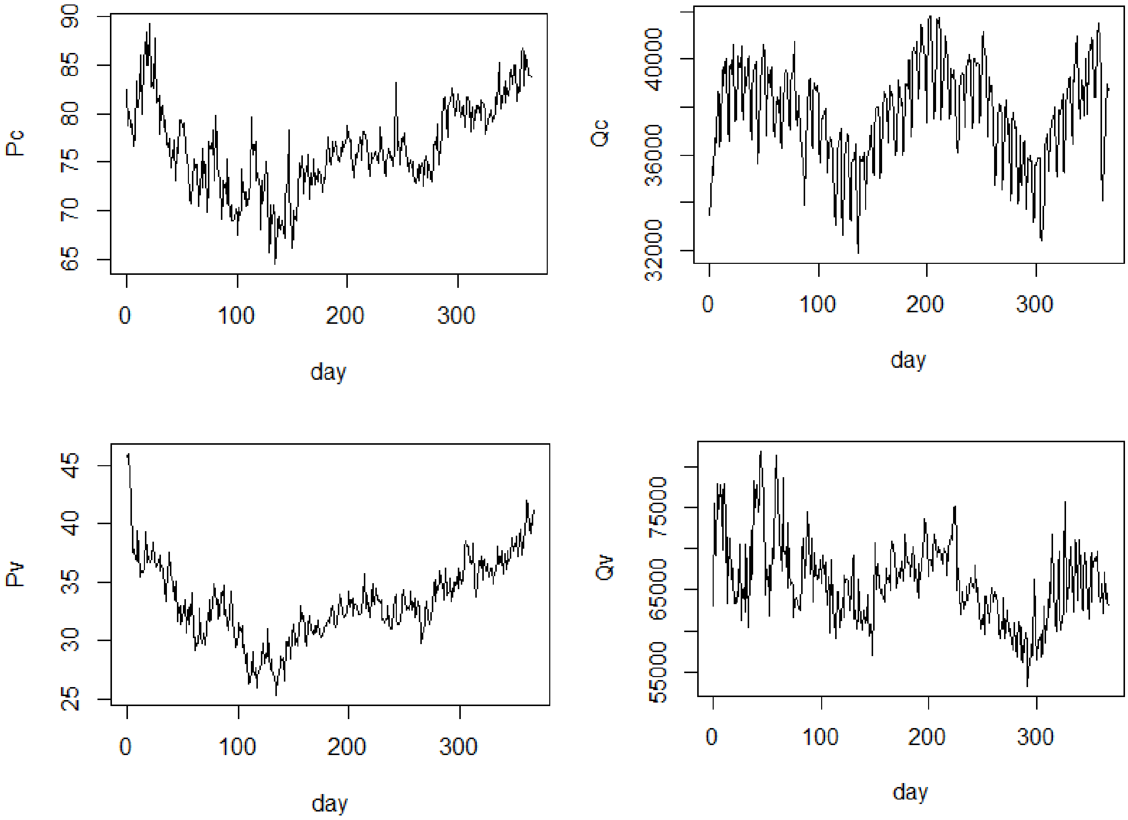
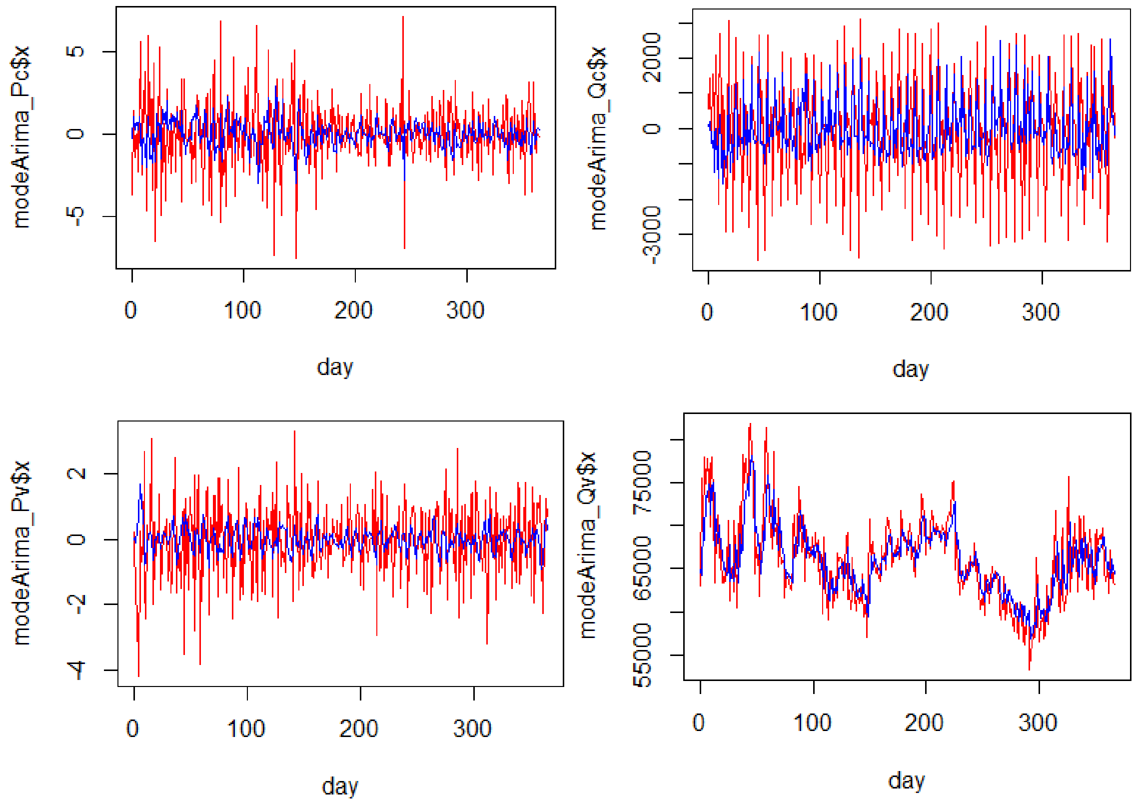
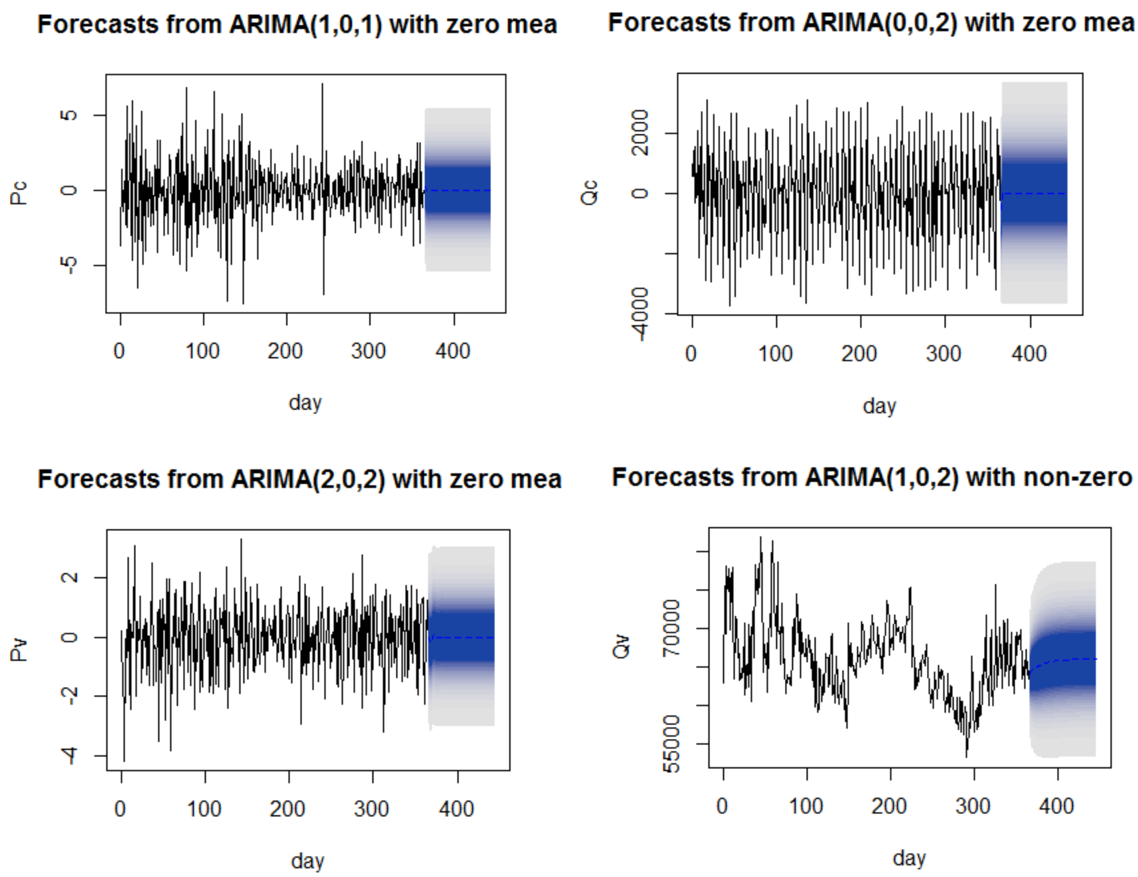
ANNEX

H1 → (12:00am-12:59am)




```
data:  Pc
Dickey-Fuller = -1.9188, Lag order = 7, p-value = 0.6112
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.9677, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -2.9419, Lag order = 7, p-value = 0.1794
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.0584, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.9844, Lag order = 7, p-value = 0.5835
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.3998, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.3142, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.1833, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```


modeArima_Pc$x
modeArima_Qc$x
modeArima_Pv$x
modeArima_Qv$x
day


Forecasts from ARIMA(1,0,1) with zero mea
Forecasts from ARIMA(0,0,2) with zero mea
Forecasts from ARIMA(2,0,2) with zero mea
Forecasts from ARIMA(1,0,2) with non-zero
Pc
Qc
Pv
Qv
day

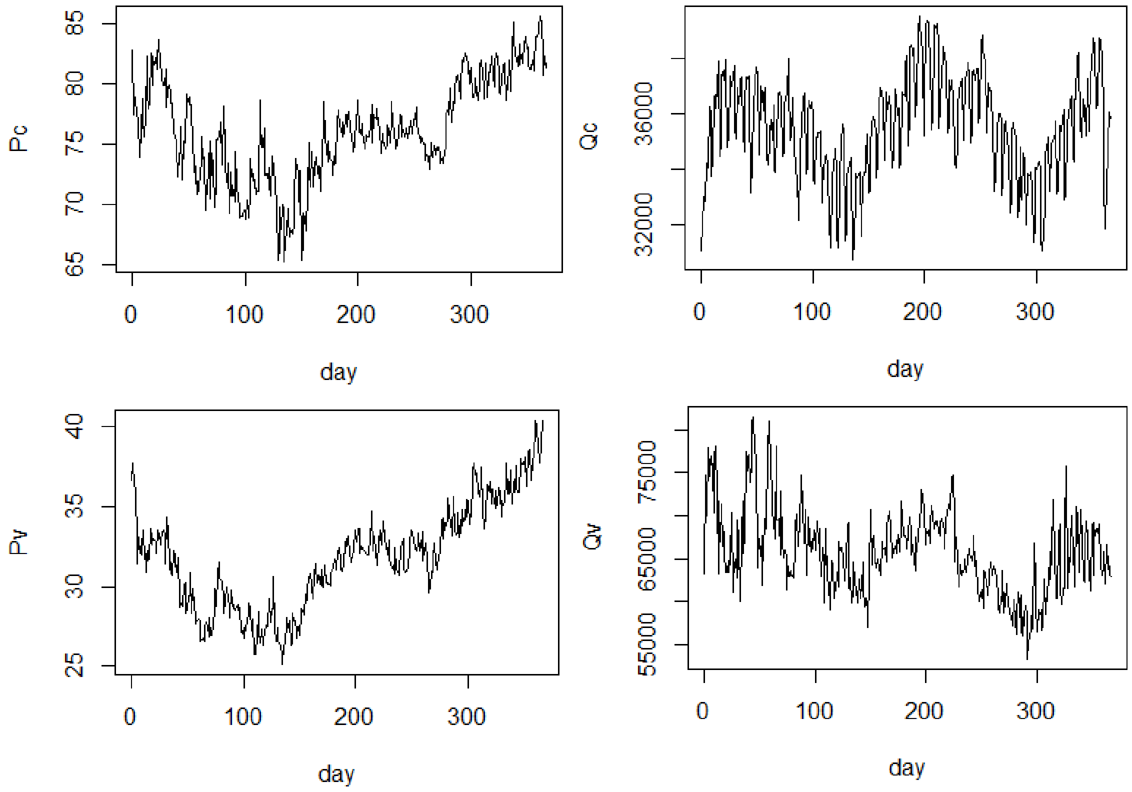
```
arima(x = diff(Pc), order = c(1, 0, 1))

Coefficients:
         ar1      ma1  intercept
      0.3789  -0.7572     0.0099
s.e.  0.0955   0.0683     0.0401

sigma^2 estimated as 3.789:  log likelihood = -761.17,  aic = 1530.35
```

```
arima(x = diff(Qc), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.0760  -0.6504     6.3121
s.e.   0.0405   0.0402    17.2604

sigma^2 estimated as 1411077:  log likelihood = -3102.66,  aic = 6213.32
```

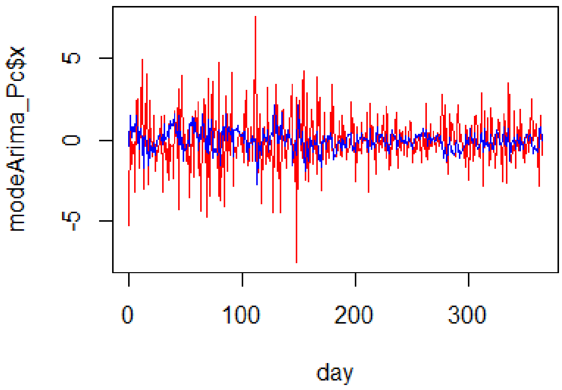
```
arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      1.2402  -0.6051  -1.4740  0.7087    -0.0134
s.e.  0.1115   0.1187   0.1146  0.0919     0.0374

sigma^2 estimated as 1.227:  log likelihood = -555.36,  aic = 1122.71
```

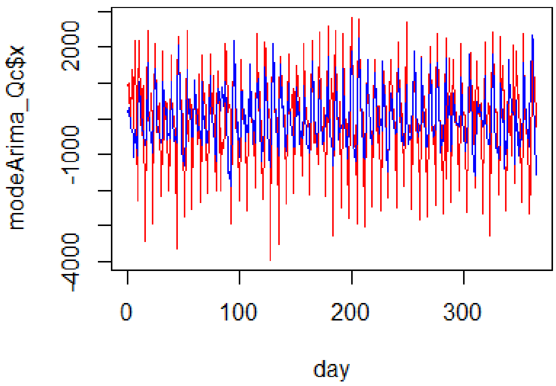
```
arima(x = Qv, order = c(1, 0, 2))

Coefficients:
         ar1      ma1      ma2  intercept
      0.9363  -0.4121  -0.1229  65966.206
s.e.  0.0247   0.0604   0.0597   1172.896

sigma^2 estimated as 10111097:  log likelihood = -3471.47,  aic = 6952.94
```

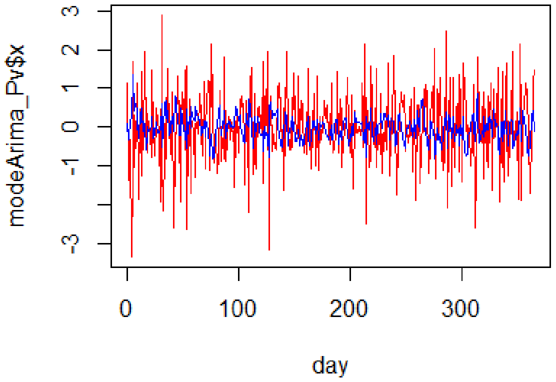
H2 → (1:00am-1:59am)

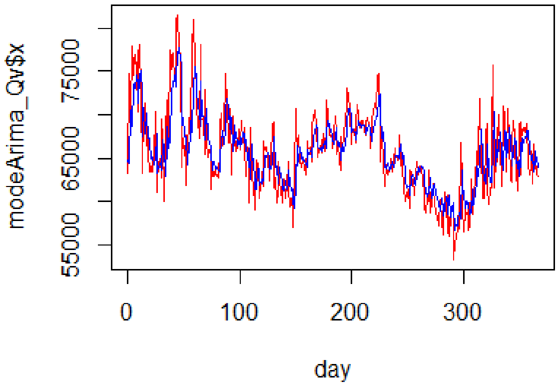


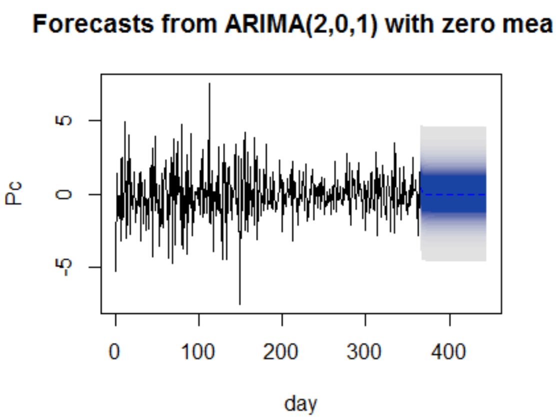

```
data:  Pc
Dickey-Fuller = -2.2301, Lag order = 7, p-value = 0.4798
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -8.7131, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -2.9806, Lag order = 7, p-value = 0.163
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -6.8787, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -2.164, Lag order = 7, p-value = 0.5077
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.5997, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.3346, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.1706, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

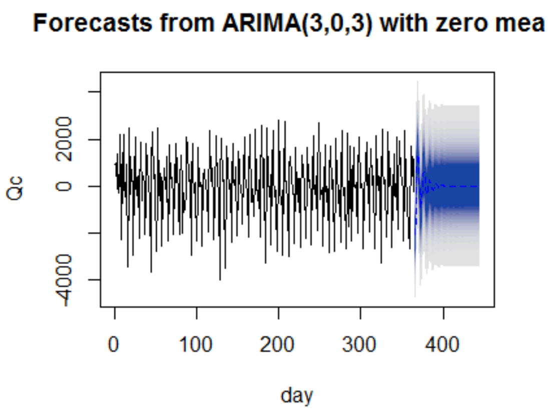

modeArima_Pc$x
5
0
-5
0
100
200
300
day

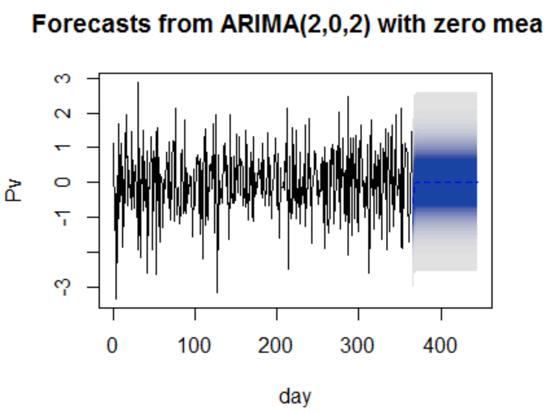

modeArima_Qc$x
2000
-1000
-4000
0
100
200
300
day

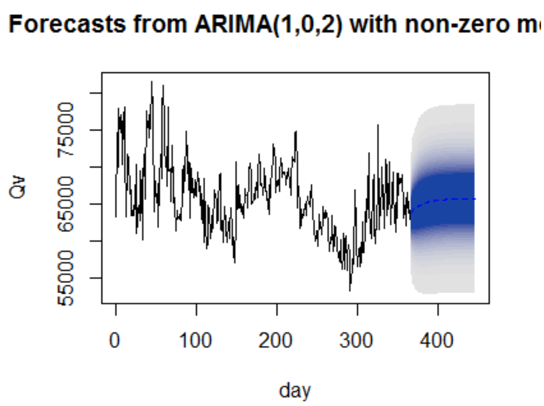

modeArima_Pv$x
3
2
1
0
-1
-3
0
100
200
300
day


modeArima_Qv$x
75000
65000
55000
0
100
200
300
day


Forecasts from ARIMA(2,0,1) with zero mea
Pc
5
0
-5
0
100
200
300
400
day


Forecasts from ARIMA(3,0,3) with zero mea
Qc
2000
0
-4000
0
100
200
300
400
day


Forecasts from ARIMA(2,0,2) with zero mea
Pv
3
2
1
0
-1
-3
0
100
200
300
400
day


Forecasts from ARIMA(1,0,2) with non-zero m
Qv
75000
65000
55000
0
100
200
300
400
day

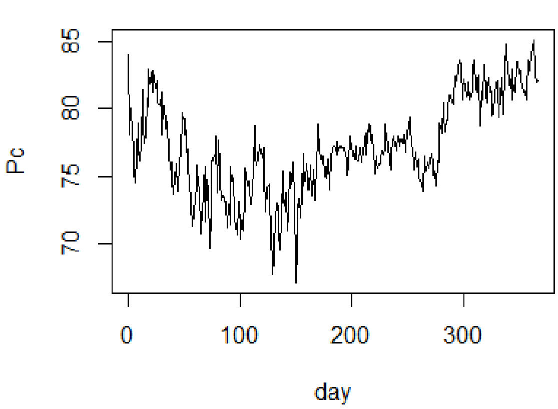
```
arima(x = diff(Pc), order = c(2, 0, 1))

Coefficients:
         ar1     ar2      ma1  intercept
      0.5160  0.1126  -0.8770     0.0081
s.e.  0.0873  0.0674   0.0661     0.0291

sigma^2 estimated as 2.728:  log likelihood = -701.21,  aic = 1412.42
```

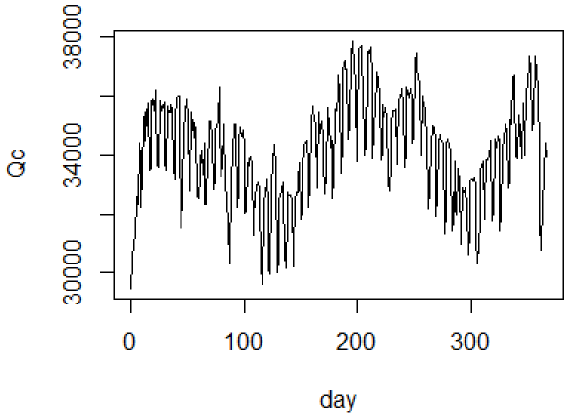
```
arima(x = diff(Qc), order = c(3, 0, 3))

Coefficients:
         ar1      ar2      ar3      ma1      ma2     ma3  intercept
      0.5106  -0.0270  -0.5130  -0.5763  -0.5311  0.6876     8.2827
s.e.  0.0718   0.0735   0.0689   0.0603   0.0536  0.0447    30.6058

sigma^2 estimated as 1073430:  log likelihood = -3053.17,  aic = 6122.35
```

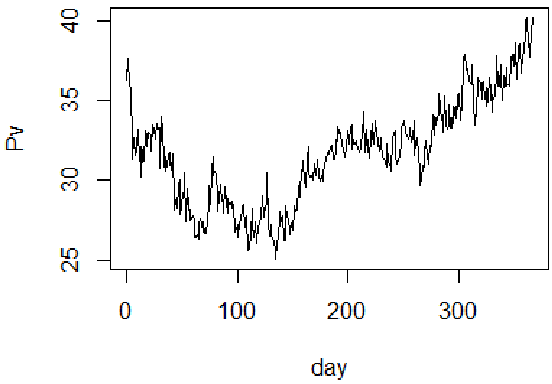
```
arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      0.9033  -0.2209  -1.2374  0.3899     0.0093
s.e.  0.9494   0.3641   0.9494  0.6719     0.0236

sigma^2 estimated as 0.8732:  log likelihood = -493.27,  aic = 998.55
```

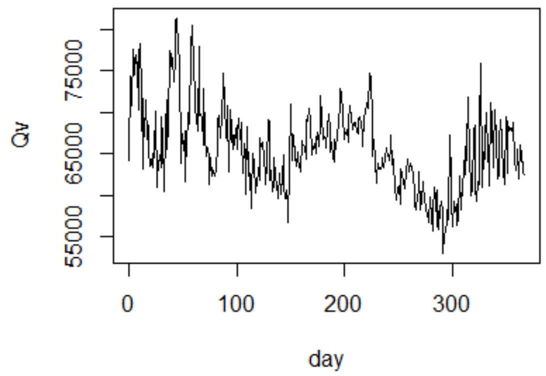
```
arima(x = Qv, order = c(1, 0, 2))

Coefficients:
         ar1      ma1      ma2  intercept
      0.9365  -0.3988  -0.1306  65678.345
s.e.  0.0248   0.0602   0.0589   1178.249

sigma^2 estimated as 9926177:  log likelihood = -3468.1,  aic = 6946.2
```

H3 → (2:00am-2:59am)

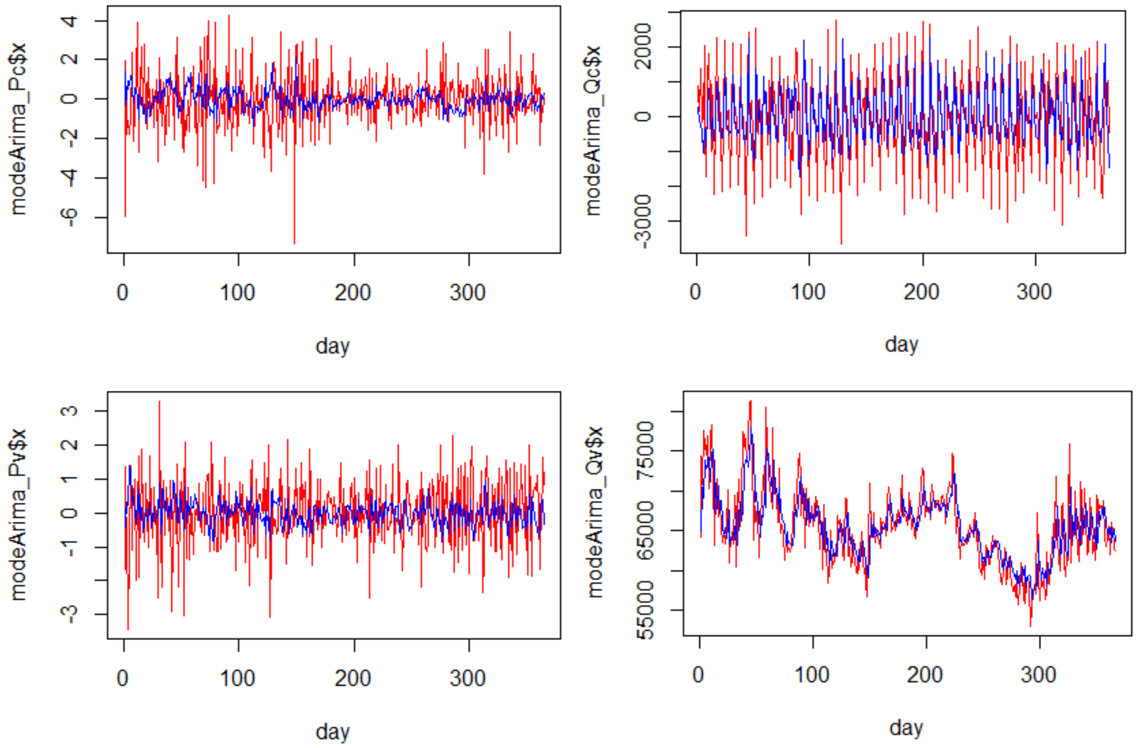


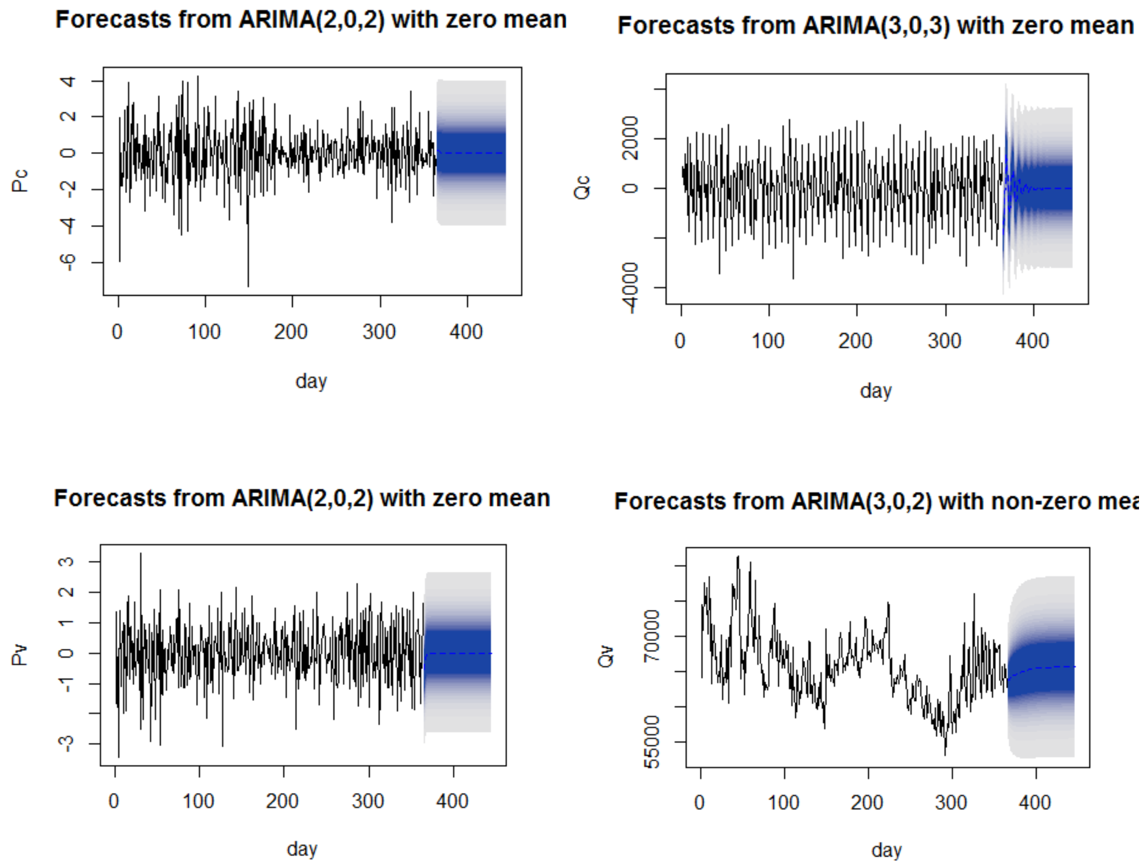







```
data:  Pc
Dickey-Fuller = -2.6265, Lag order = 7, p-value = 0.3125
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -8.2302, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -3.1535, Lag order = 7, p-value = 0.09603
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -6.7644, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -2.1829, Lag order = 7, p-value = 0.4998
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.4518, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.3432, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.2268, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```


modeArima_Pc$x
modeArima_Qc$x
modeArima_Pv$x
modeArima_Qv$x
day


Forecasts from ARIMA(2,0,2) with zero mean
Forecasts from ARIMA(3,0,3) with zero mean
Forecasts from ARIMA(2,0,2) with zero mean
Forecasts from ARIMA(3,0,2) with non-zero mea
Pc
Qc
Pv
Qv
day

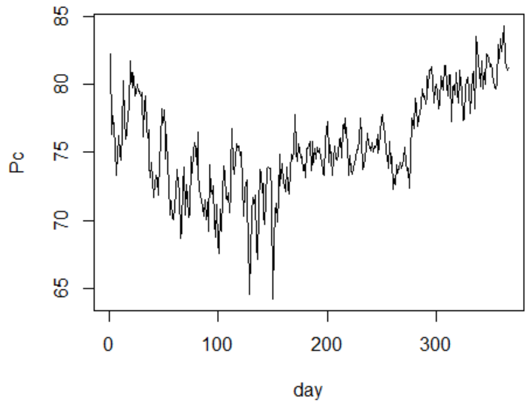
```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
         ar1     ar2      ma1      ma2  intercept
      0.1001  0.3747  -0.4081  -0.4337     0.0075
s.e.  0.6112  0.3329   0.6243   0.5265     0.0234

sigma^2 estimated as 2.122:  log likelihood = -655.45,  aic = 1322.9
```

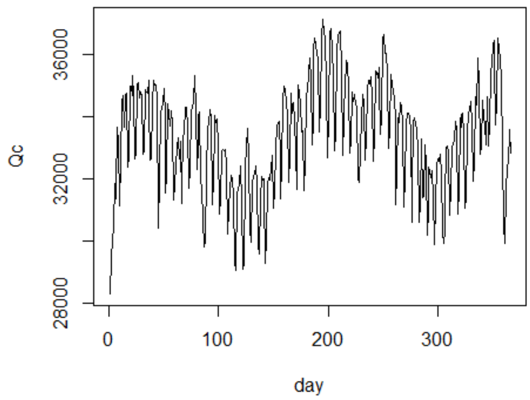
```
arima(x = diff(Qc), order = c(3, 0, 3))

Coefficients:
         ar1      ar2      ar3      ma1      ma2     ma3  intercept
      0.5409  -0.0750  -0.5323  -0.5431  -0.5054  0.7020     8.9608
s.e.  0.0732   0.0789   0.0730   0.0619   0.0588  0.0441    30.5522

sigma^2 estimated as 905331:  log likelihood = -3022.19,  aic = 6060.38
```

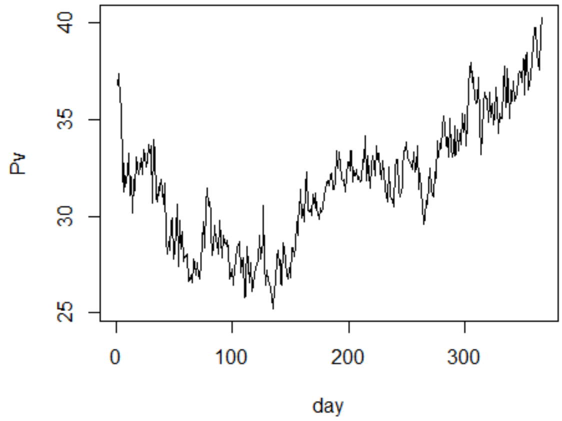
```
arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      1.1036  -0.2227  -1.4700  0.5239     0.0102
s.e.  0.3770   0.1715   0.3695  0.2694     0.0227

sigma^2 estimated as 0.8978:  log likelihood = -498.35,  aic = 1008.69
```

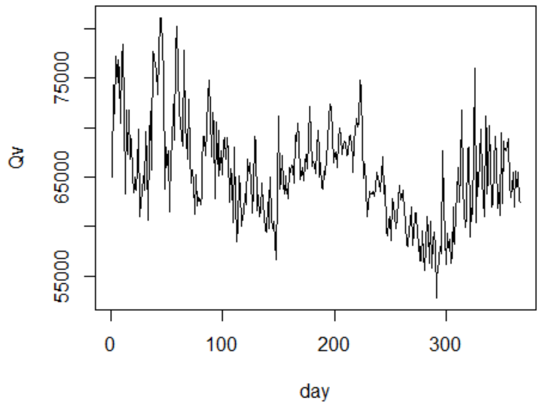
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.4150  0.6244  -0.1253  0.1294  -0.4791  65597.130
s.e.  0.7392  1.0074   0.3132  0.7311   0.5848   1203.109

sigma^2 estimated as 9899636:  log likelihood = -3467.62,  aic = 6949.24
```

H4 → (3:00am-3:59am)

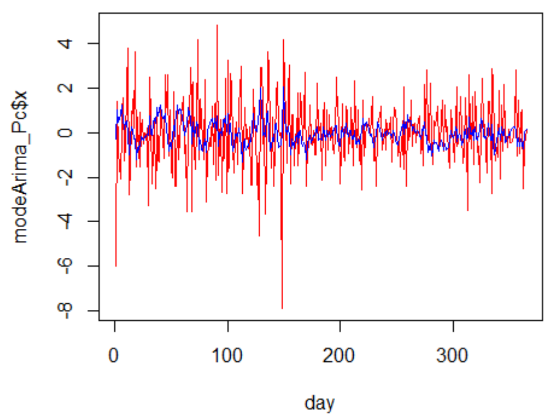


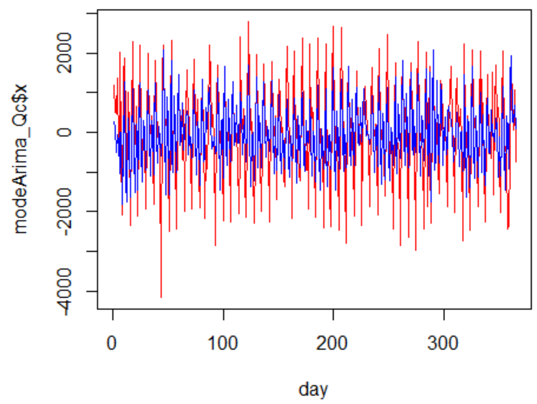


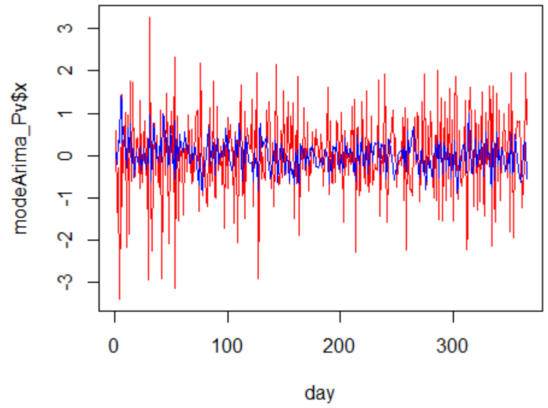


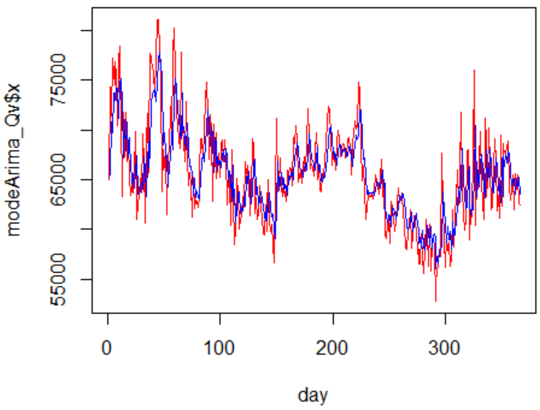


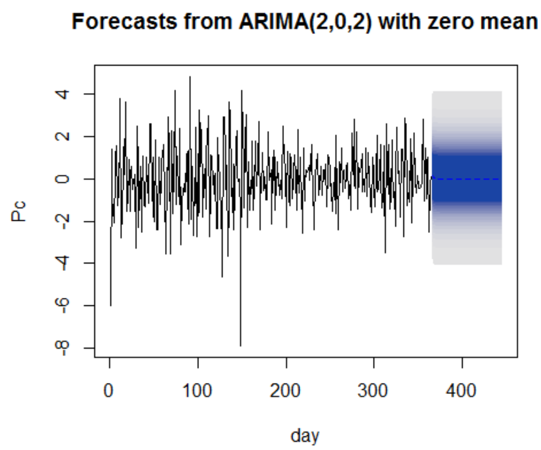

```
data:  Pc
Dickey-Fuller = -2.7237, Lag order = 7, p-value = 0.2715
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -8.1962, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -3.1689, Lag order = 7, p-value = 0.09341
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -6.7465, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -2.1709, Lag order = 7, p-value = 0.5048
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.5337, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.3533, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.3811, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

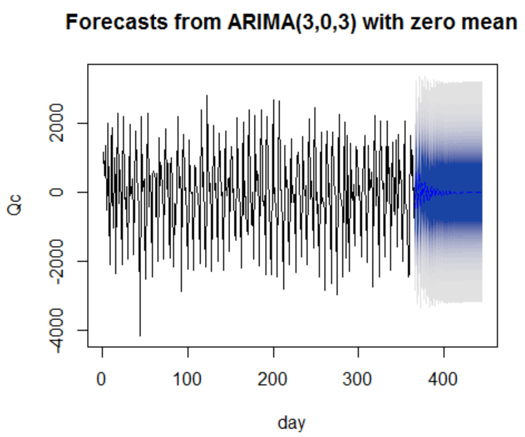

modeArima_Pc$x
day

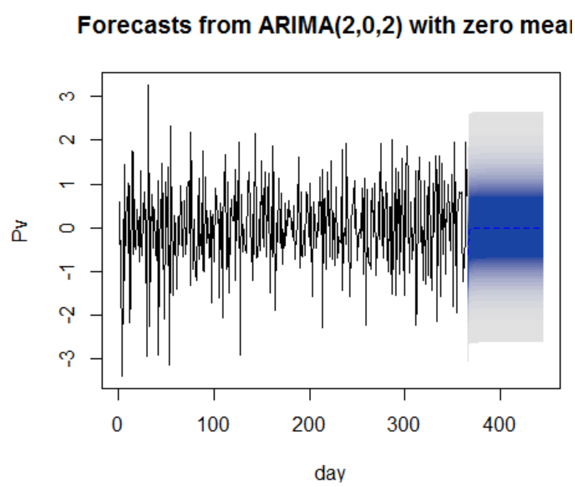

modeArima_Qc$x
day

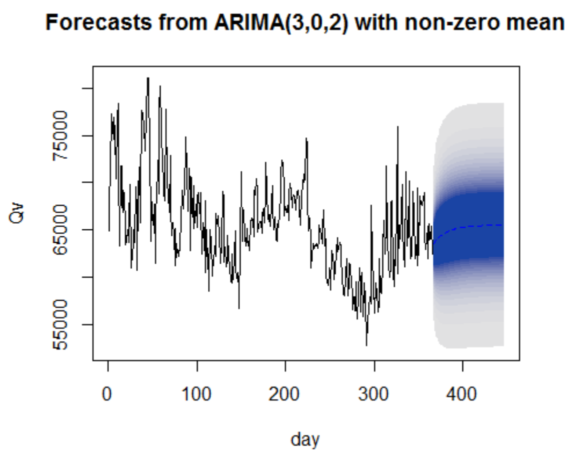

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(2,0,2) with zero mean
Pc
day


Forecasts from ARIMA(3,0,3) with zero mean
Qc
day


Forecasts from ARIMA(2,0,2) with zero mea
Pv
day


Forecasts from ARIMA(3,0,2) with non-zero mean
Qv
day

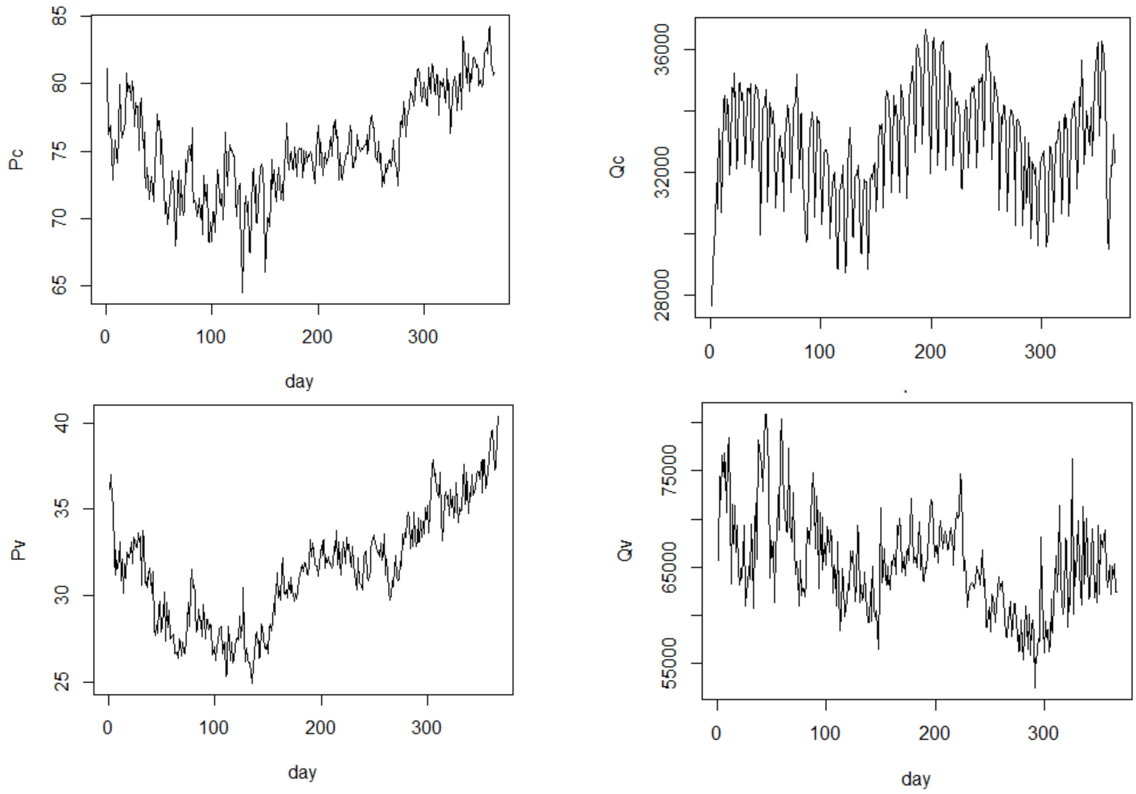
```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
         ar1     ar2      ma1      ma2  intercept
      0.2597  0.2528  -0.5203  -0.3439     0.0099
s.e.     NaN     NaN      NaN      NaN     0.0224

sigma^2 estimated as 2.262:  log likelihood = -667.1,  aic = 1346.2
```

```
arima(x = diff(Qc), order = c(3, 0, 3))

Coefficients:
         ar1      ar2     ar3      ma1     ma2      ma3  intercept
      0.1646  -0.5800  0.5305  -0.1090  0.1083  -0.7557     5.6798
s.e.  0.0825   0.0515  0.0894   0.0888  0.0752   0.0400    13.8455

sigma^2 estimated as 876767:  log likelihood = -3016.46,  aic = 6048.92
```

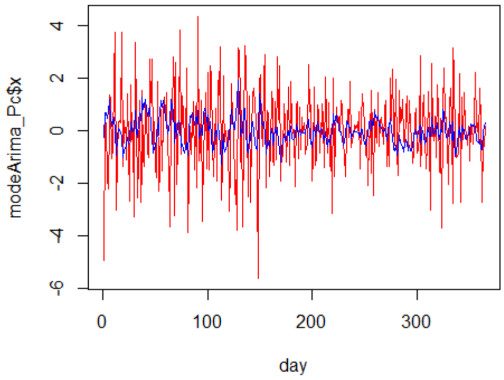
```
arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      1.0580  -0.1908  -1.4285  0.4868     0.0101
s.e.  0.3459   0.1713   0.3378  0.2554     0.0221

sigma^2 estimated as 0.9078:  log likelihood = -500.39,  aic = 1012.77
```

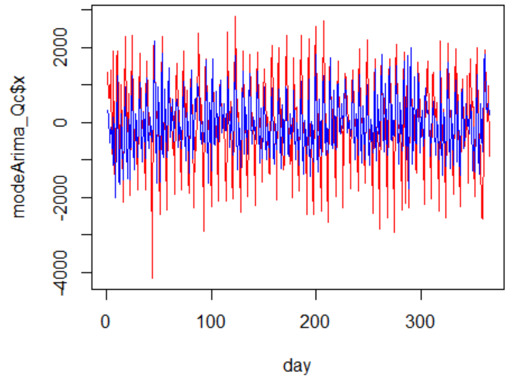
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.3399  0.7583  -0.1797  0.2116  -0.5701  65517.355
s.e.  0.2070  0.2404   0.1399  0.1947   0.1749   1248.215

sigma^2 estimated as 9898989:  log likelihood = -3467.62,  aic = 6949.25
```

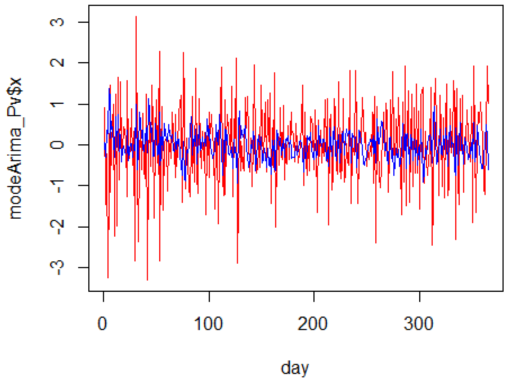
H5 → (4:00am-4:59am)

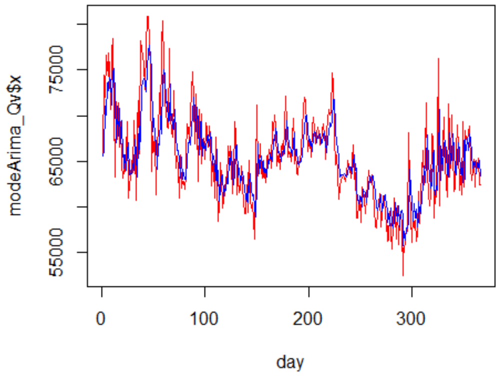


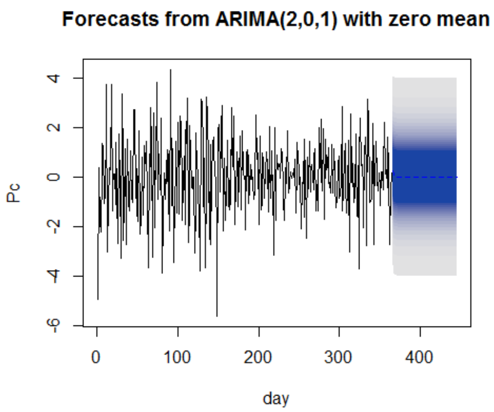

```
data:  Pc
Dickey-Fuller = -2.6621, Lag order = 7, p-value = 0.2975
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -8.3535, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -3.131, Lag order = 7, p-value = 0.09982
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -6.7759, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -2.1769, Lag order = 7, p-value = 0.5023
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.4224, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.3708, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.5211, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

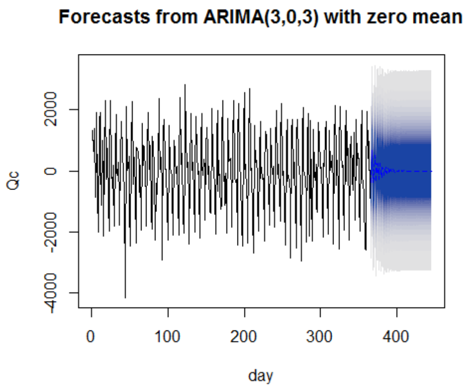

modeArima_Pc$x
day

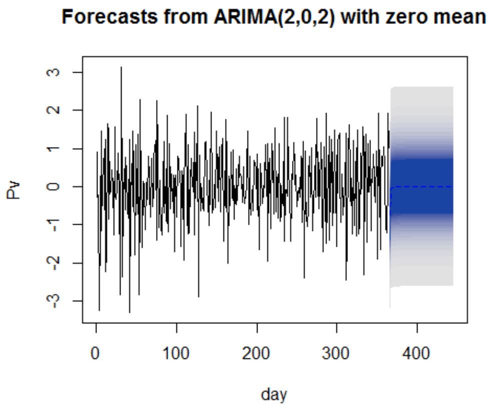

modeArima_Qc$x
day

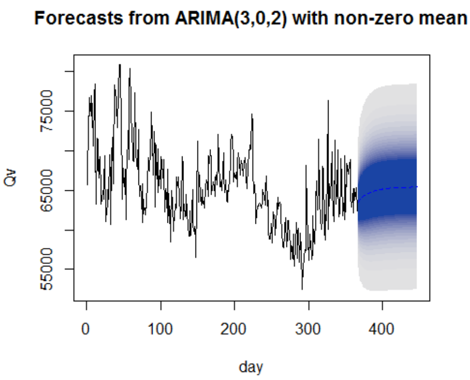

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(2,0,1) with zero mean
Pc
day

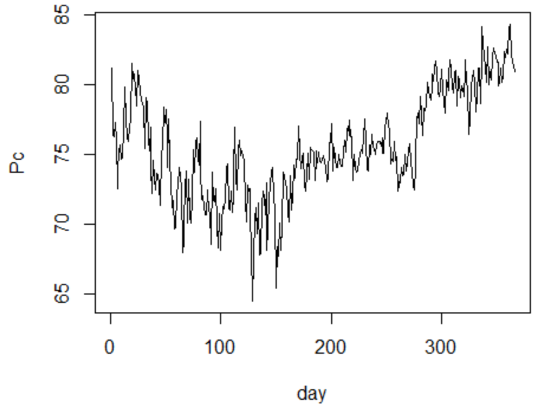

Forecasts from ARIMA(3,0,3) with zero mean
Qc
day

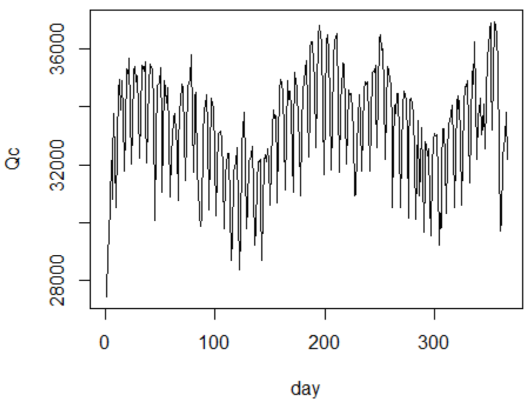

Forecasts from ARIMA(2,0,2) with zero mean
Pv
day

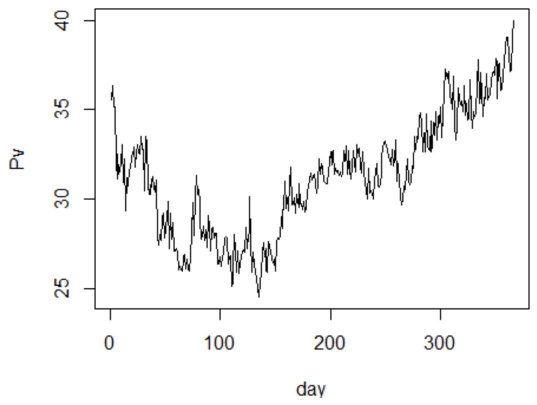

Forecasts from ARIMA(3,0,2) with non-zero mean
Qv
day

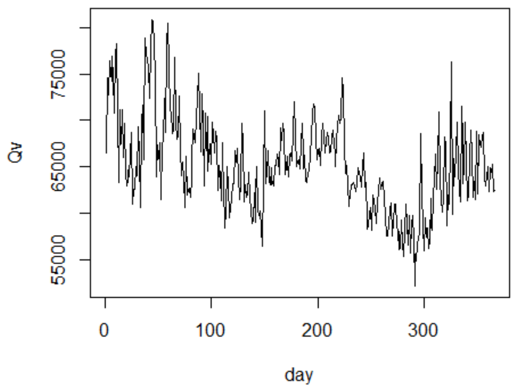
```
arima(x = diff(Pc), order = c(2, 0, 1))

Coefficients:
         ar1      ar2      ma1  intercept
      0.6561  -0.0338  -0.8942     0.0111
s.e.  0.0703   0.0599   0.0470     0.0219

sigma^2 estimated as 2.143:  log likelihood = -657.25,  aic = 1324.5


arima(x = diff(Qc), order = c(3, 0, 3))

Coefficients:
         ar1      ar2     ar3      ma1     ma2      ma3  intercept
      0.1629  -0.5595  0.5039  -0.0914  0.0626  -0.7424     5.5481
s.e.  0.0886   0.0602  0.0995   0.0999  0.0884   0.0428    13.2622

sigma^2 estimated as 923093:  log likelihood = -3025.8,  aic = 6067.6


arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      1.0251  -0.1575  -1.4032  0.4619     0.0110
s.e.  0.3096   0.1596   0.3014  0.2287     0.0221

sigma^2 estimated as 0.8919:  log likelihood = -497.14,  aic = 1006.29


arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2     ar3     ma1      ma2  intercept
      0.3508  0.7587  -0.188  0.2147  -0.5870  65422.073
s.e.  0.1684  0.1654   0.130  0.1534   0.1442   1265.099

sigma^2 estimated as 9875743:  log likelihood = -3467.21,  aic = 6948.41
```

H6 → (5:00am-5:59am)

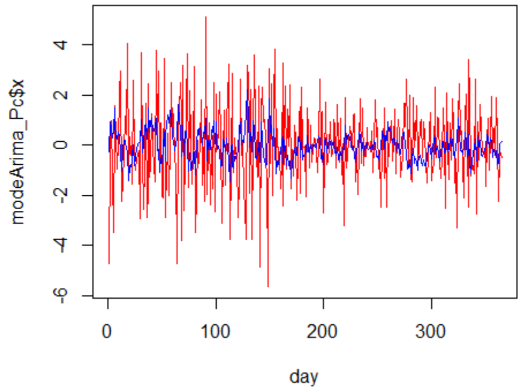


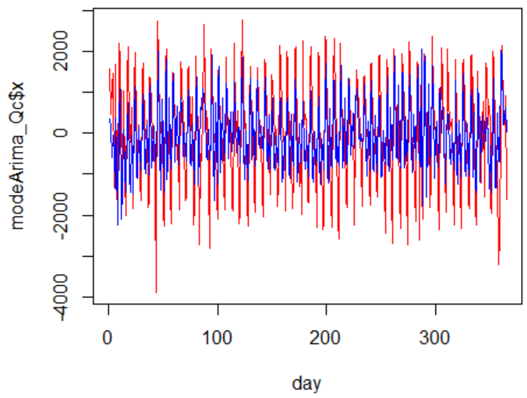


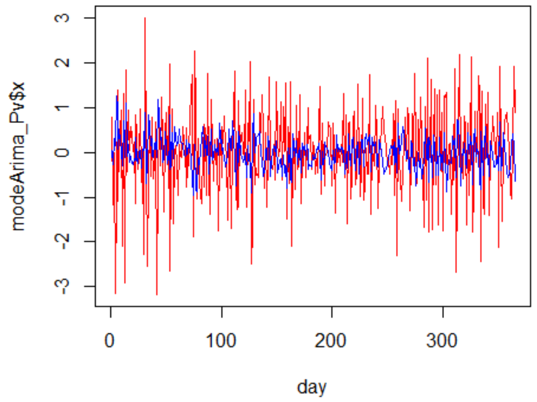


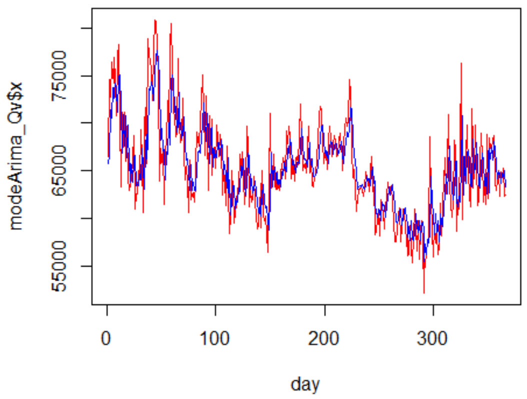



```
data:  Pc
Dickey-Fuller = -2.6492, Lag order = 7, p-value = 0.3029
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -8.2003, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -3.2774, Lag order = 7, p-value = 0.07506
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -6.7657, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -2.2558, Lag order = 7, p-value = 0.469
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.6249, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.3571, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.6269, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

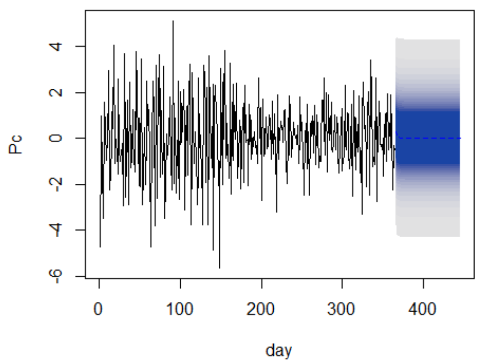




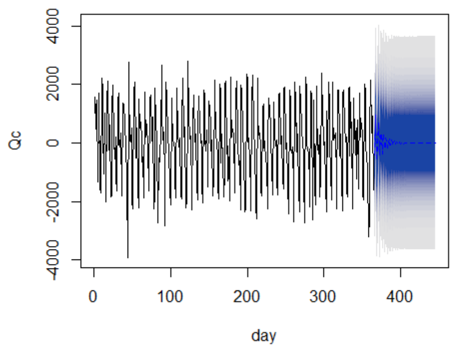




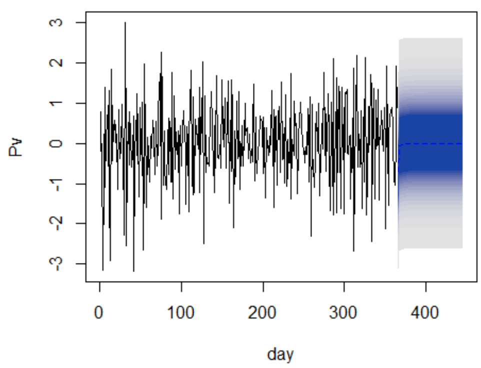
Forecasts from ARIMA(2,0,1) with zero mean



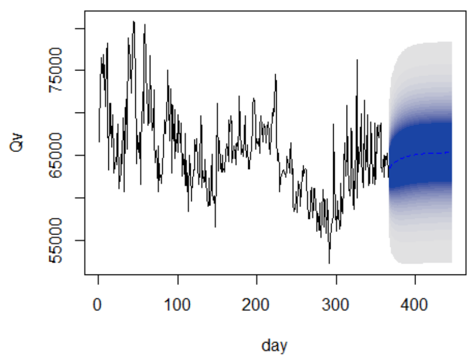
Forecasts from ARIMA(3,0,3) with zero mean



Forecasts from ARIMA(2,0,2) with zero mean

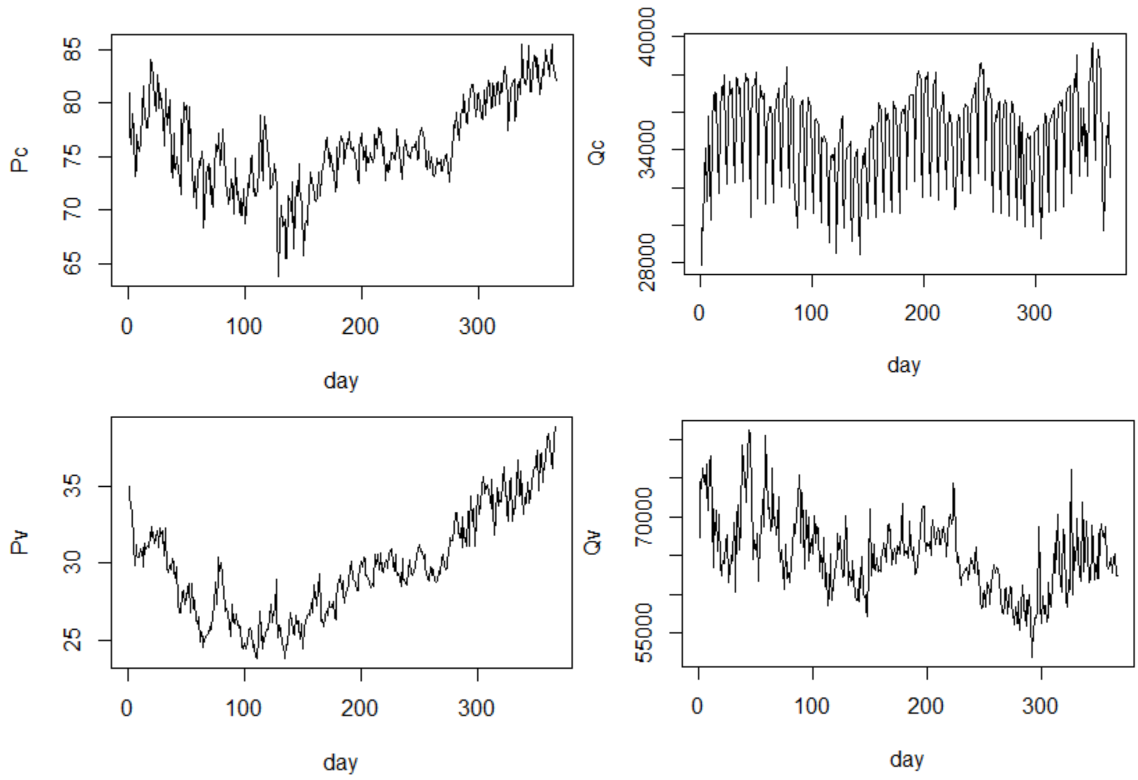


Forecasts from ARIMA(3,0,2) with non-zero mean

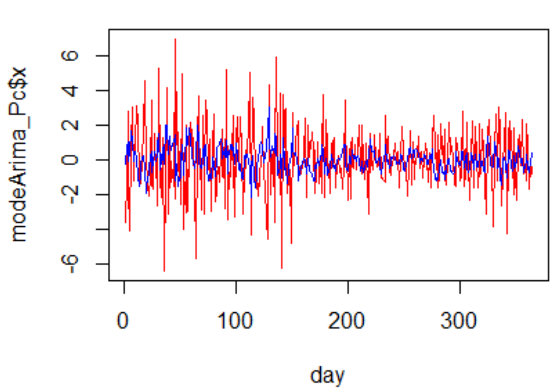


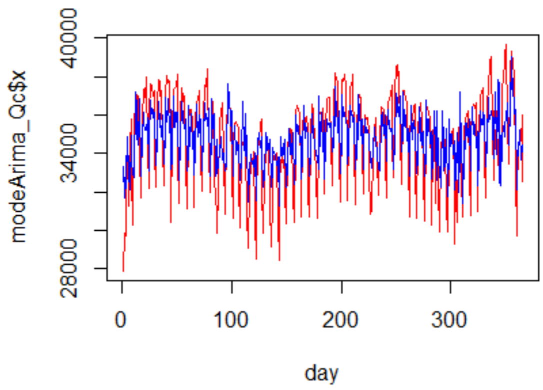
```
arima(x = diff(Pc), order = c(2, 0, 1))

Coefficients:
       ar1     ar2      ma1  intercept
      0.60  0.0350  -0.9017     0.0112
s.e.  0.07  0.0604   0.0450     0.0225

sigma^2 estimated as 2.445:  log likelihood = -681.29,  aic = 1372.58


arima(x = diff(Qc), order = c(3, 0, 3))

Coefficients:
         ar1      ar2     ar3      ma1     ma2      ma3  intercept
      0.2911  -0.5325  0.6368  -0.2343  0.0594  -0.8251     2.2859
s.e.  0.0519   0.0514  0.0625   0.0600  0.0815   0.0396     2.2377

sigma^2 estimated as 1162883:  log likelihood = -3069.64,  aic = 6155.28


arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      0.9137  -0.0754  -1.2986  0.3684     0.0117
s.e.  0.2922   0.1575   0.2855  0.2208     0.0215

sigma^2 estimated as 0.8835:  log likelihood = -495.42,  aic = 1002.83


arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.3764  0.7409  -0.1928  0.2058  -0.5935  65331.479
s.e.  0.1608  0.1508   0.1296  0.1450   0.1392   1277.202

sigma^2 estimated as 9791457:  log likelihood = -3465.65,  aic = 6945.3
```

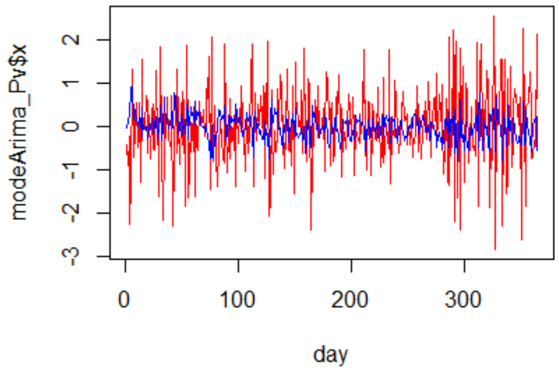
H7 → (6:00am-6:59am)

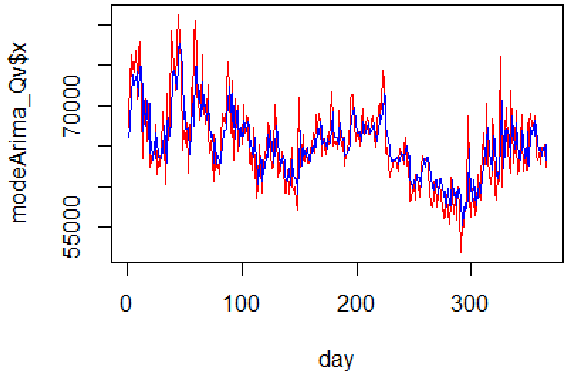


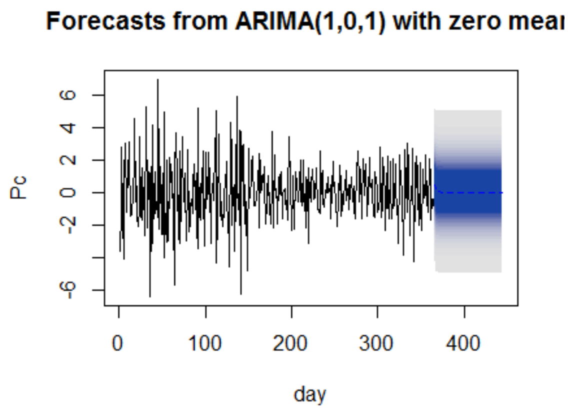

```
data:  Pc
Dickey-Fuller = -2.385, Lag order = 7, p-value = 0.4144
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.749, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -3.5823, Lag order = 7, p-value = 0.03491
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.2801, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -1.9282, Lag order = 7, p-value = 0.6073
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.9877, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.3619, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.6619, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

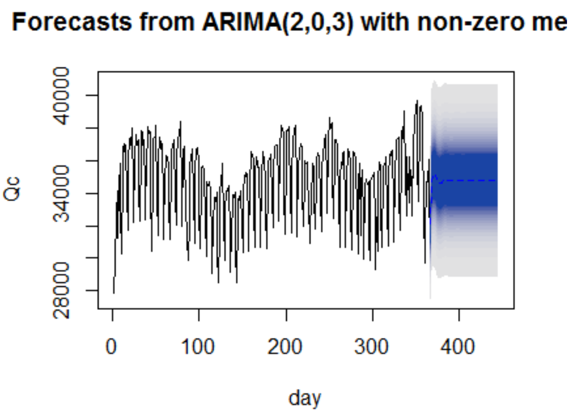

modeArima_Pc$x
day

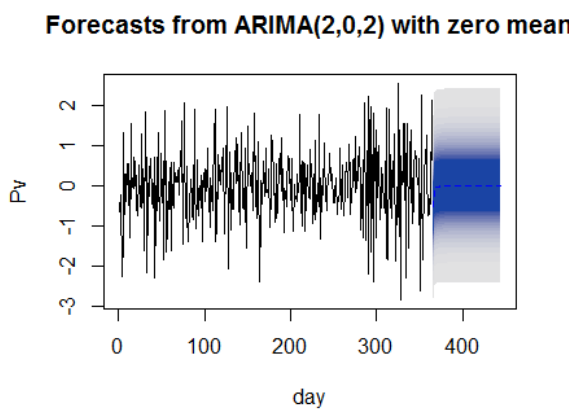

modeArima_Qc$x
day

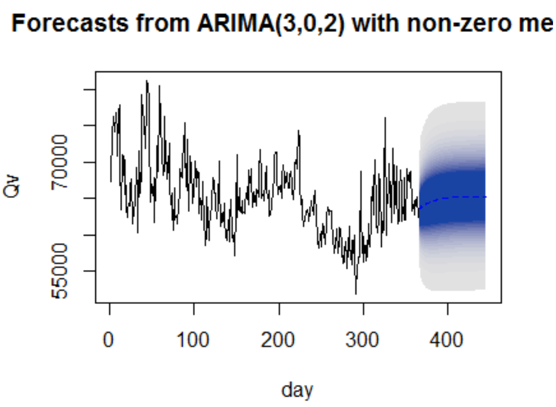

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(1,0,1) with zero meai
Pc
day


Forecasts from ARIMA(2,0,3) with non-zero me
Qc
day


Forecasts from ARIMA(2,0,2) with zero mean
Pv
day


Forecasts from ARIMA(3,0,2) with non-zero me
Qv
day

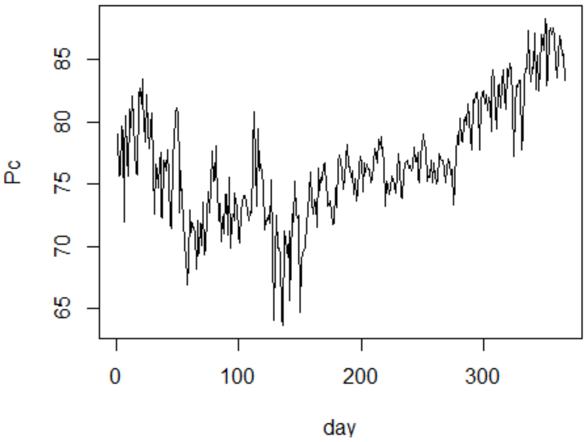
```
arima(x = diff(Pc), order = c(1, 0, 1))

Coefficients:
         ar1      ma1  intercept
      0.5059  -0.8474     0.0133
s.e.  0.0856   0.0556     0.0294

sigma^2 estimated as 3.222:  log likelihood = -731.65,  aic = 1471.31
```

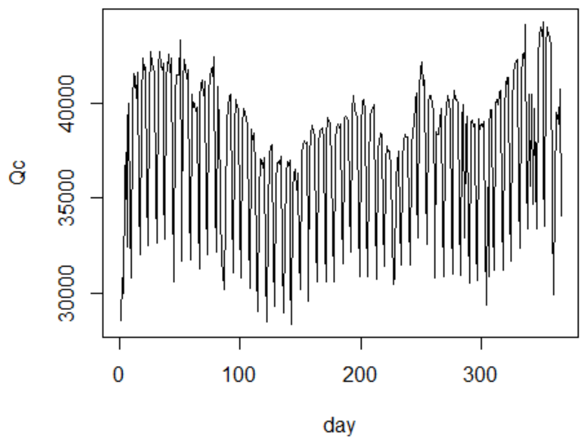
```
arima(x = Qc, order = c(2, 0, 3))

Coefficients:
         ar1      ar2      ma1      ma2     ma3   intercept
      1.5333  -0.7391  -0.9033  -0.4326  0.7461  34761.9121
s.e.  0.0588   0.0566   0.0473   0.0592  0.0357    187.2484

sigma^2 estimated as 3251448:  log likelihood = -3264.25,  aic = 6542.5
```

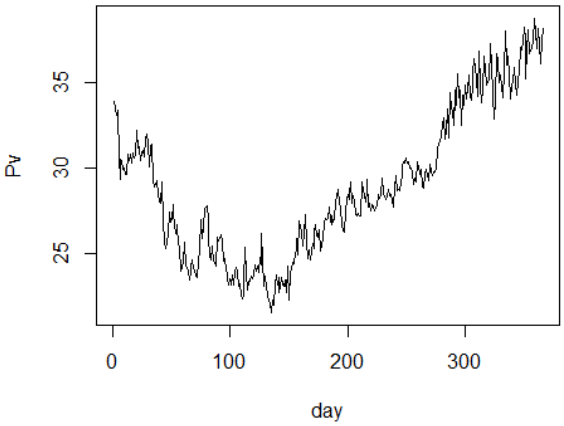
```
arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      0.9892  -0.1408  -1.3148  0.3832     0.0119
s.e.  0.2796   0.1673   0.2715  0.2161     0.0210

sigma^2 estimated as 0.7752:  log likelihood = -471.55,  aic = 955.1
```

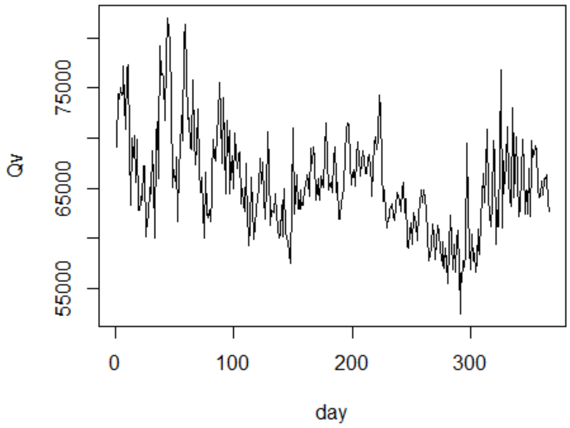
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.4083  0.6964  -0.1801  0.1971  -0.5806  65299.163
s.e.  0.1575  0.1475   0.1313  0.1414   0.1390   1272.132

sigma^2 estimated as 9523635:  log likelihood = -3460.59,  aic = 6935.19
```

H8 → (7:00am-7:59am)

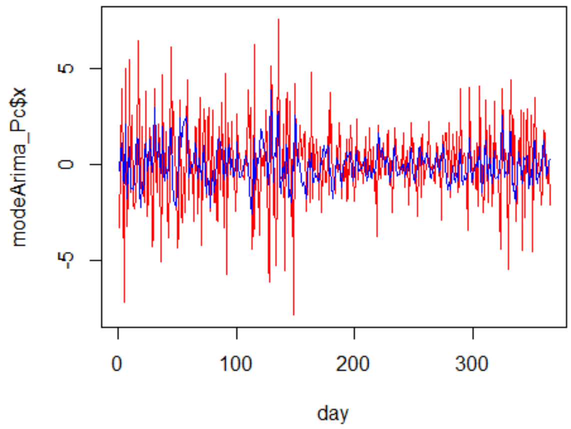


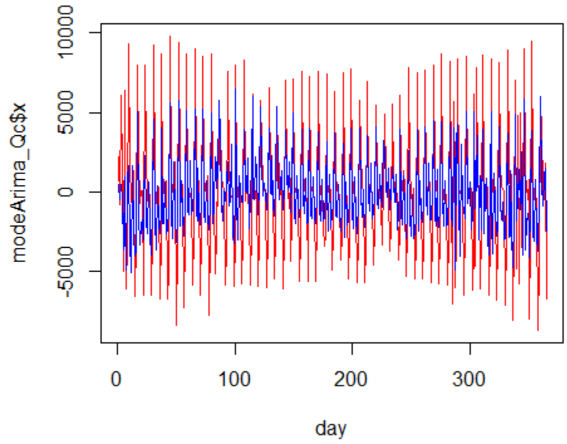


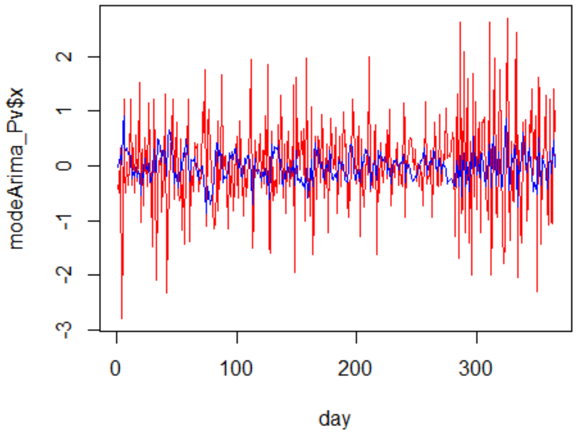


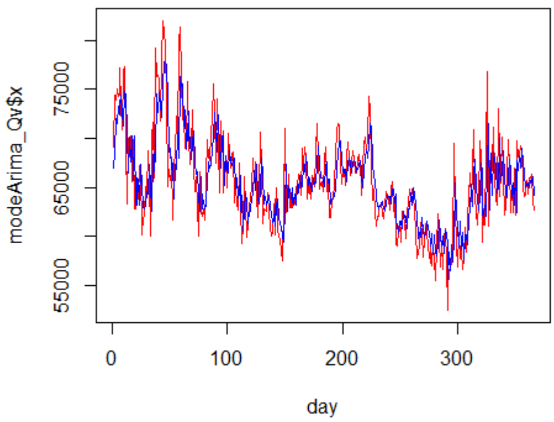



```
data:  Pc
Dickey-Fuller = -2.6905, Lag order = 7, p-value = 0.2855
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.5367, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -3.2369, Lag order = 7, p-value = 0.08191
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.885, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -2.0572, Lag order = 7, p-value = 0.5528
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -9.124, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.4425, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.749, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

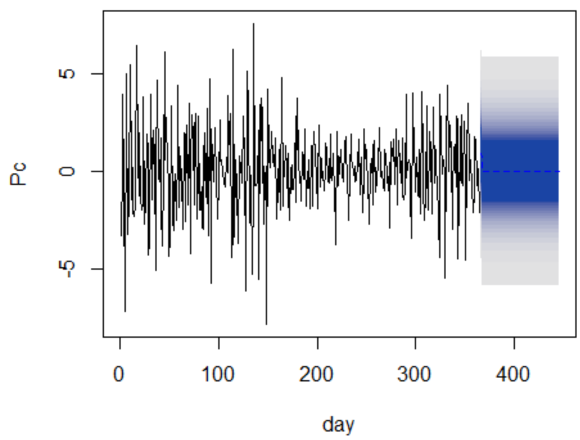




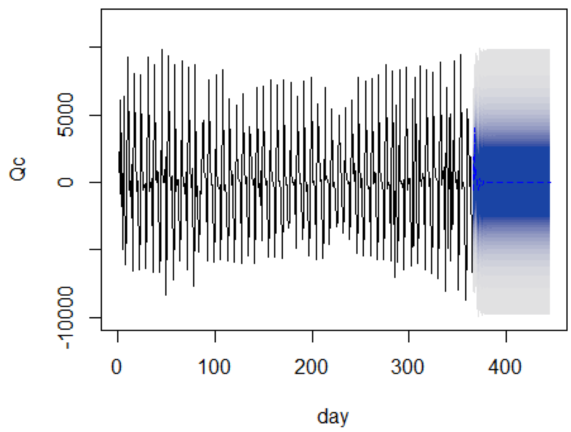




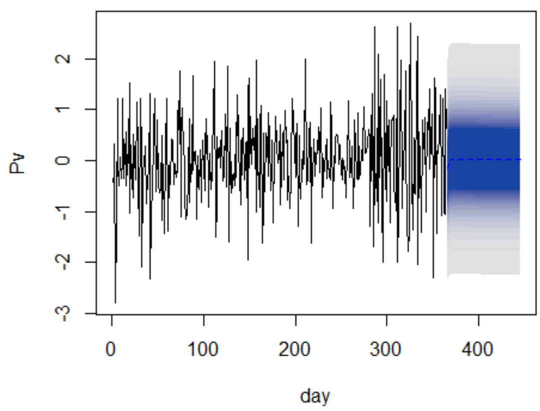
Forecasts from ARIMA(0,0,2) with zero mean



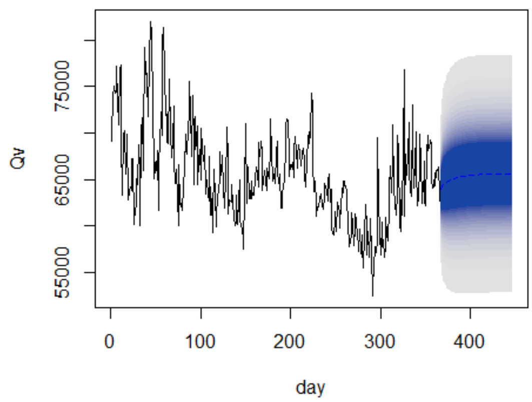
Forecasts from ARIMA(2,0,4) with zero mean



Forecasts from ARIMA(2,0,2) with zero mean



Forecasts from ARIMA(3,0,2) with non-zero mea



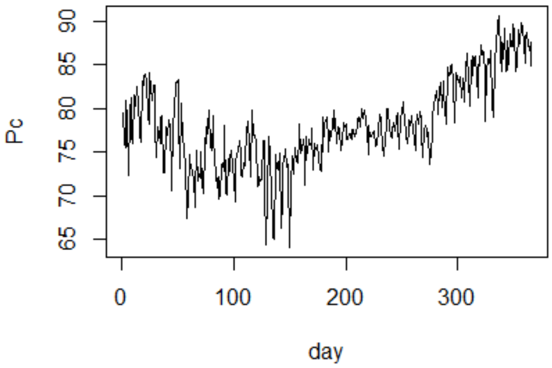
```
arima(x = diff(Pc), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.3601  -0.3066     0.0202
s.e.   0.0500   0.0514     0.0360

sigma^2 estimated as 4.192:  log likelihood = -779.74,  aic = 1567.49
```

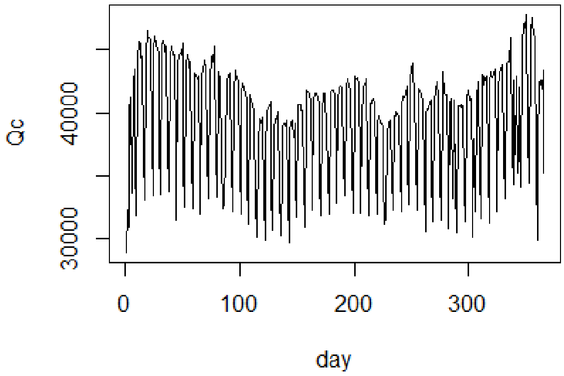
```
arima(x = diff(Qc), order = c(2, 0, 4))

Coefficients:
         ar1      ar2      ma1     ma2     ma3      ma4  intercept
      0.1340  -0.5495  -0.4583  0.1759  0.0933  -0.7427     3.0059
s.e.  0.0816   0.0560   0.0648  0.0568  0.0539   0.0376     8.4492

sigma^2 estimated as 8418384:  log likelihood = -3430.14,  aic = 6876.28
```

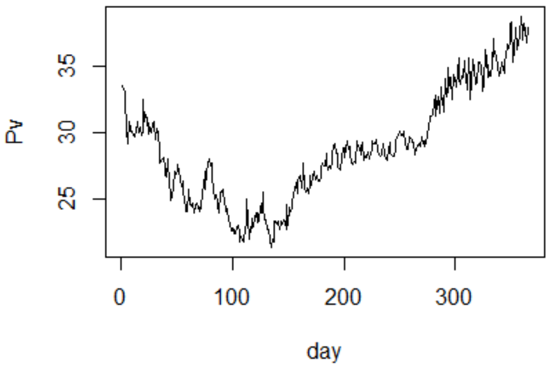
```
arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      1.5178  -0.5230  -1.7916  0.7972     0.0072
s.e.  0.1008   0.0998   0.0732  0.0723     0.0416

sigma^2 estimated as 0.6934:  log likelihood = -451.31,  aic = 914.62
```

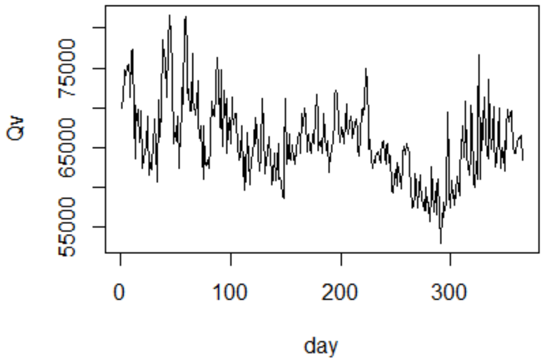
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.4145  0.6793  -0.1783  0.2265  -0.5818  65601.962
s.e.  0.1520  0.1107   0.1273  0.1356   0.1326   1178.502

sigma^2 estimated as 9303565:  log likelihood = -3456.33,  aic = 6926.66
```

H9 → (8:00am-8:59am)

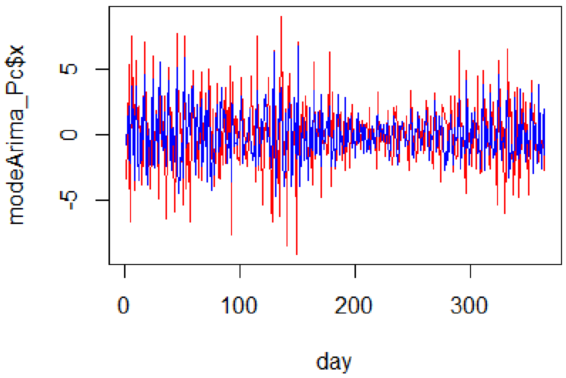


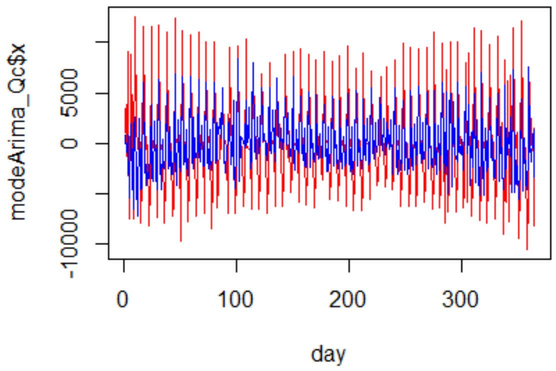


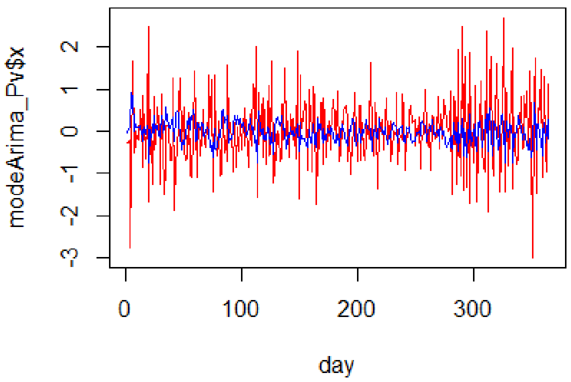


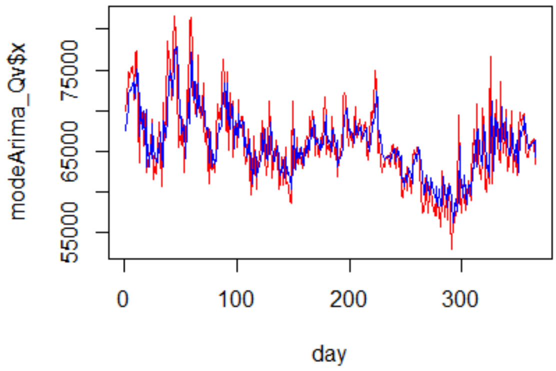


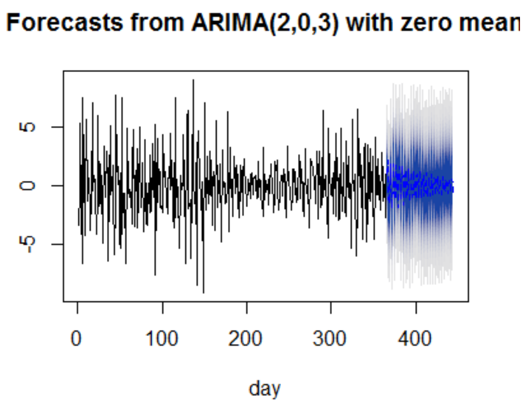

```
data:  Pc
Dickey-Fuller = -2.3599, Lag order = 7, p-value = 0.425
alternative hypothesis: stationary


data:  diff(Pc)
Dickey-Fuller = -7.4174, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -3.2373, Lag order = 7, p-value = 0.08184
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -8.4728, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -2.1014, Lag order = 7, p-value = 0.5341
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.6644, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.3224, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.7707, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

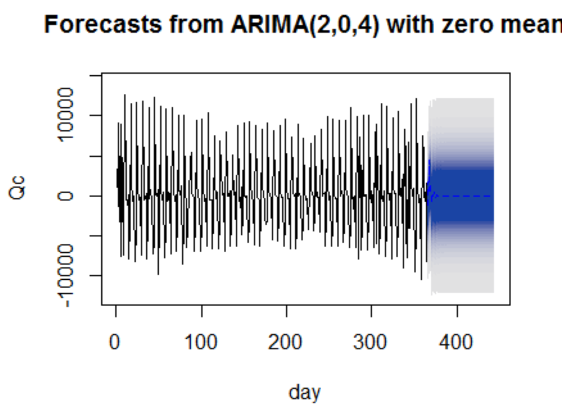

modeArima_Pc$x
day

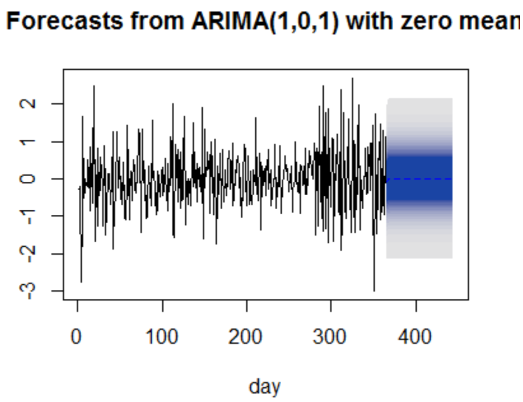

modeArima_Qc$x
day

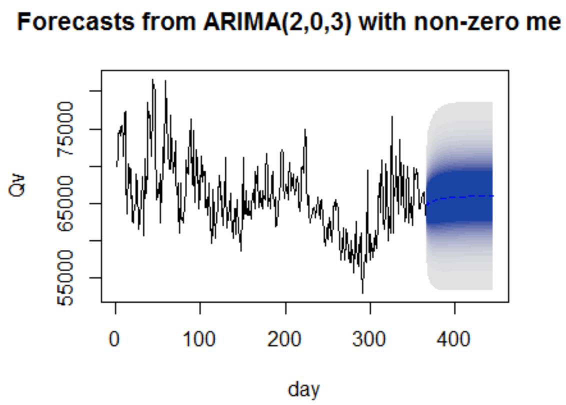

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(2,0,3) with zero mean
Pc
day


Forecasts from ARIMA(2,0,4) with zero mean
Qc
day


Forecasts from ARIMA(1,0,1) with zero mean
Pv
day


Forecasts from ARIMA(2,0,3) with non-zero me
Qv
day

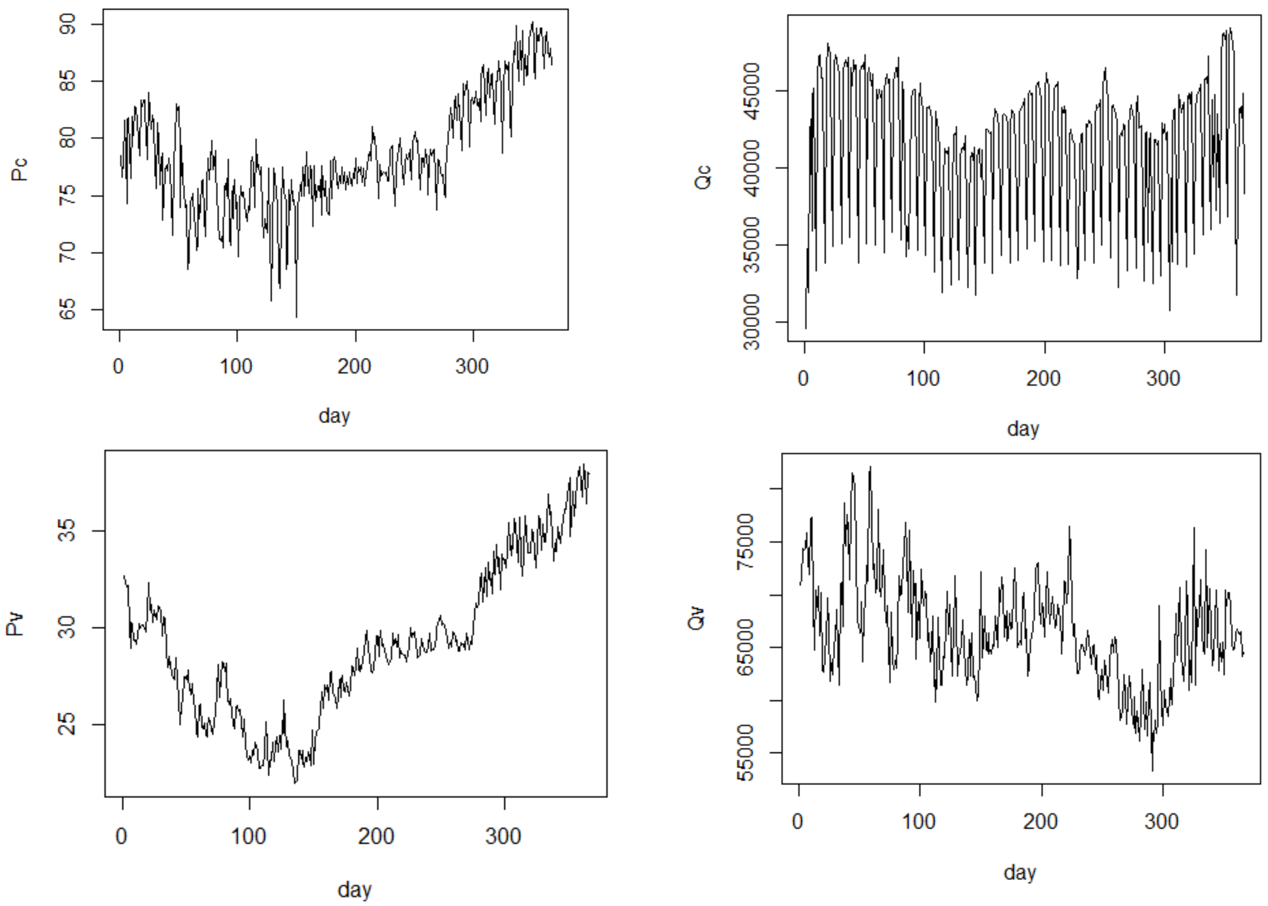
```
arima(x = diff(Pc), order = c(2, 0, 3))

Coefficients:
          ar1      ar2      ma1     ma2      ma3  intercept
      -0.4587  -0.9682  -0.0455  0.5860  -0.5996     0.0240
s.e.   0.0172   0.0155   0.0718  0.0491   0.0772     0.0471

sigma^2 estimated as 5.344:  log likelihood = -825.39,  aic = 1664.78
```

```
arima(x = diff(Qc), order = c(2, 0, 4))

Coefficients:
         ar1      ar2      ma1     ma2     ma3      ma4  intercept
      0.1302  -0.5494  -0.4904  0.1894  0.0939  -0.7516    -0.1669
s.e.  0.0622   0.0585   0.0528  0.0650  0.0552   0.0430     7.0026

sigma^2 estimated as 12463024:  log likelihood = -3502.09,  aic = 7020.17
```

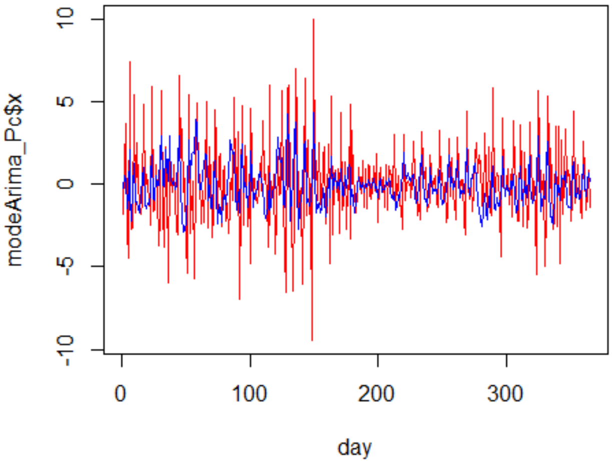
```
arima(x = diff(Pv), order = c(1, 0, 1))

Coefficients:
         ar1      ma1  intercept
      0.3154  -0.6252     0.0129
s.e.  0.1206   0.0987     0.0226

sigma^2 estimated as 0.6196:  log likelihood = -430.64,  aic = 869.29
```

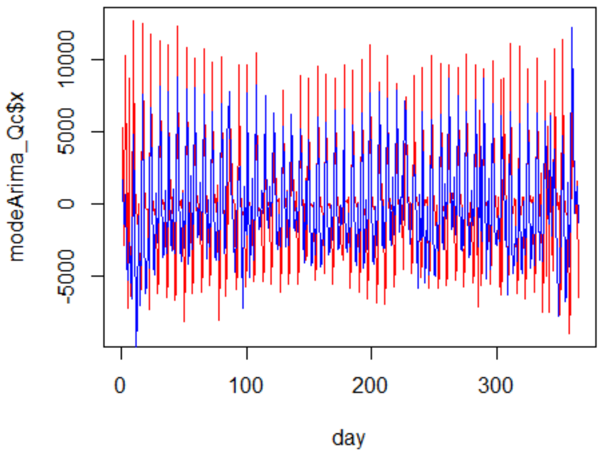
```
arima(x = Qv, order = c(2, 0, 3))

Coefficients:
         ar1     ar2     ma1      ma2      ma3  intercept
      0.1076  0.7748  0.5451  -0.4991  -0.1483  65947.174
s.e.  0.0855  0.0840  0.1031   0.0804   0.0746   1164.914

sigma^2 estimated as 9095325:  log likelihood = -3452.2,  aic = 6918.41
```

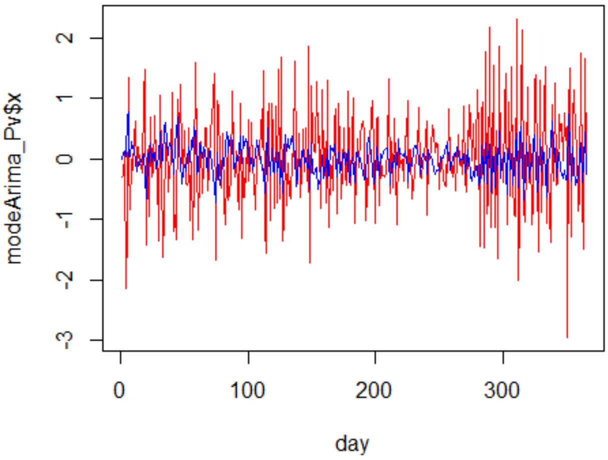
H10 → (9:00am-9:59am)

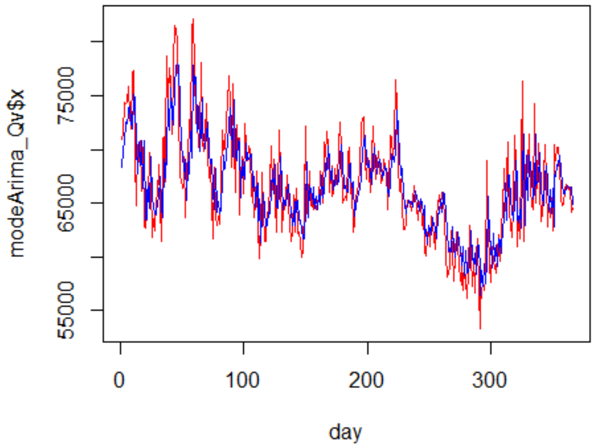


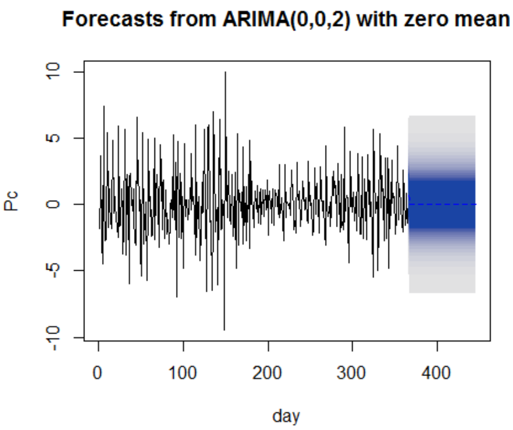

```
data:  Pc
Dickey-Fuller = -2.3697, Lag order = 7, p-value = 0.4209
alternative hypothesis: stationary


data:  diff(Pc)
Dickey-Fuller = -7.5367, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -3.2671, Lag order = 7, p-value = 0.07679
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -8.5251, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.9516, Lag order = 7, p-value = 0.5974
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.4023, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.2514, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.8433, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

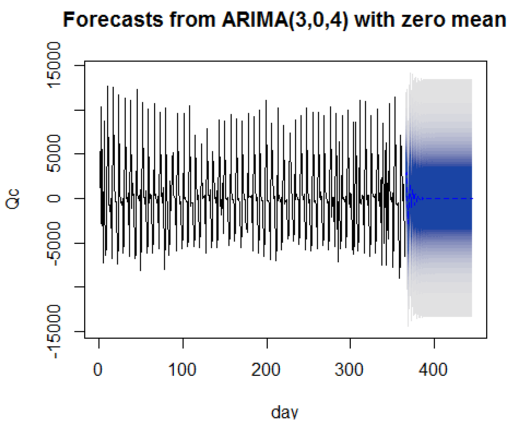

modeArima_Pc$x
day

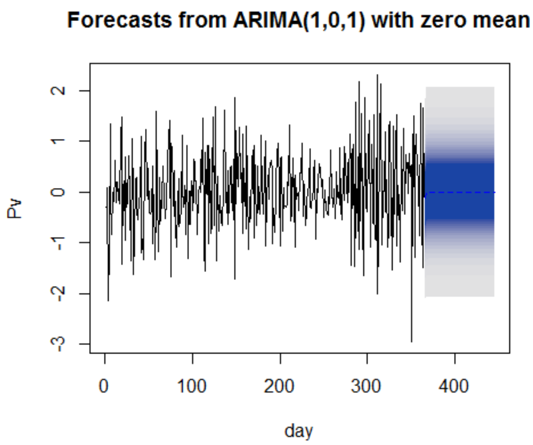

modeArima_Qc$x
day

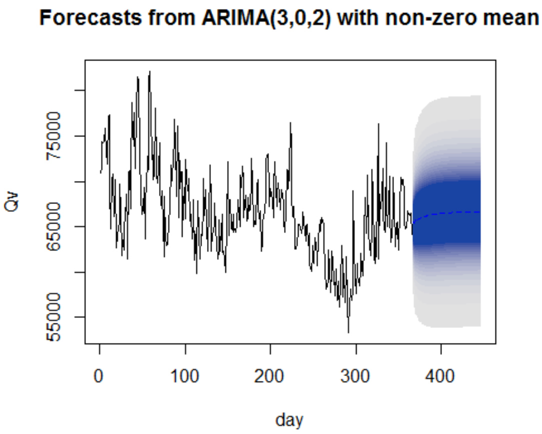

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(0,0,2) with zero mean
Pc
day


Forecasts from ARIMA(3,0,4) with zero mean
Qc
day


Forecasts from ARIMA(1,0,1) with zero mean
Pv
day


Forecasts from ARIMA(3,0,2) with non-zero mean
Qv
day

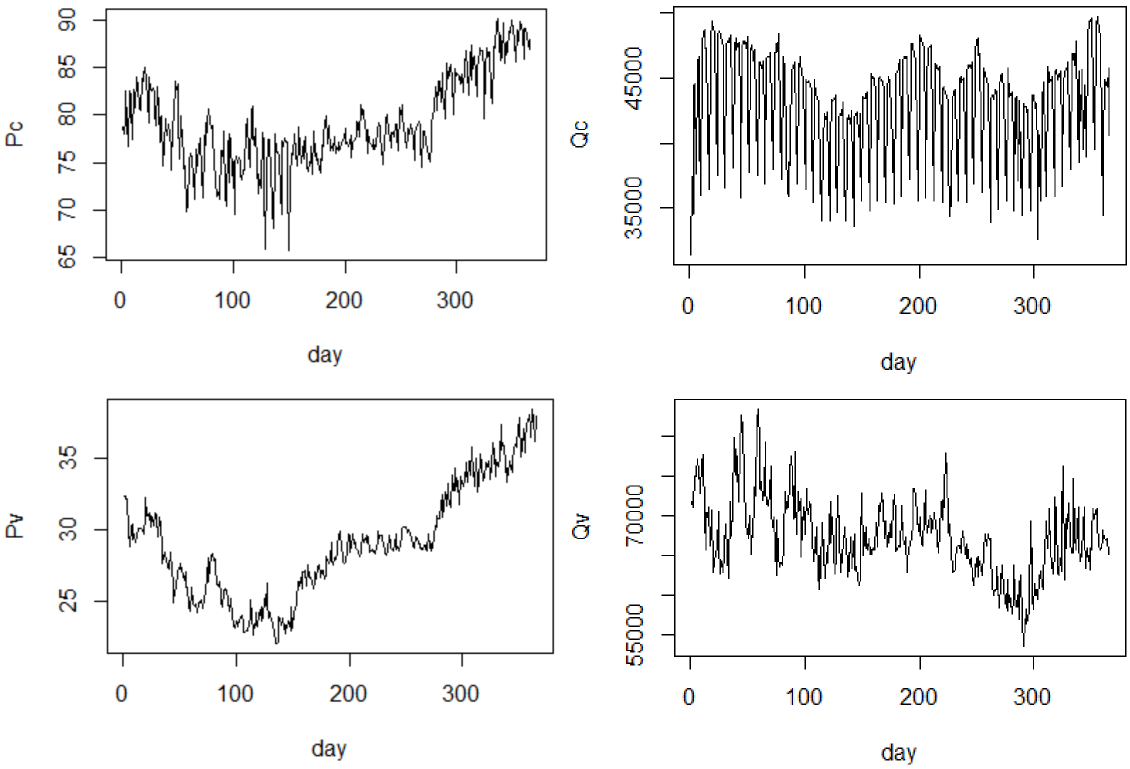
```
arima(x = diff(Pc), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.444  -0.3319     0.0245
s.e.   0.049   0.0498     0.0269

sigma^2 estimated as 5.106:  log likelihood = -815.88,  aic = 1639.76
```

```
arima(x = diff(Qc), order = c(3, 0, 4))

Coefficients:
         ar1      ar2     ar3      ma1     ma2      ma3     ma4  intercept
      0.3403  -0.3717  0.5219  -0.8485  0.0339  -0.8184  0.6953    10.3662
s.e.  0.1358   0.0807  0.1167   0.1239  0.0755   0.0503  0.0912    23.2264

sigma^2 estimated as 12575008:  log likelihood = -3503.08,  aic = 7024.15
```

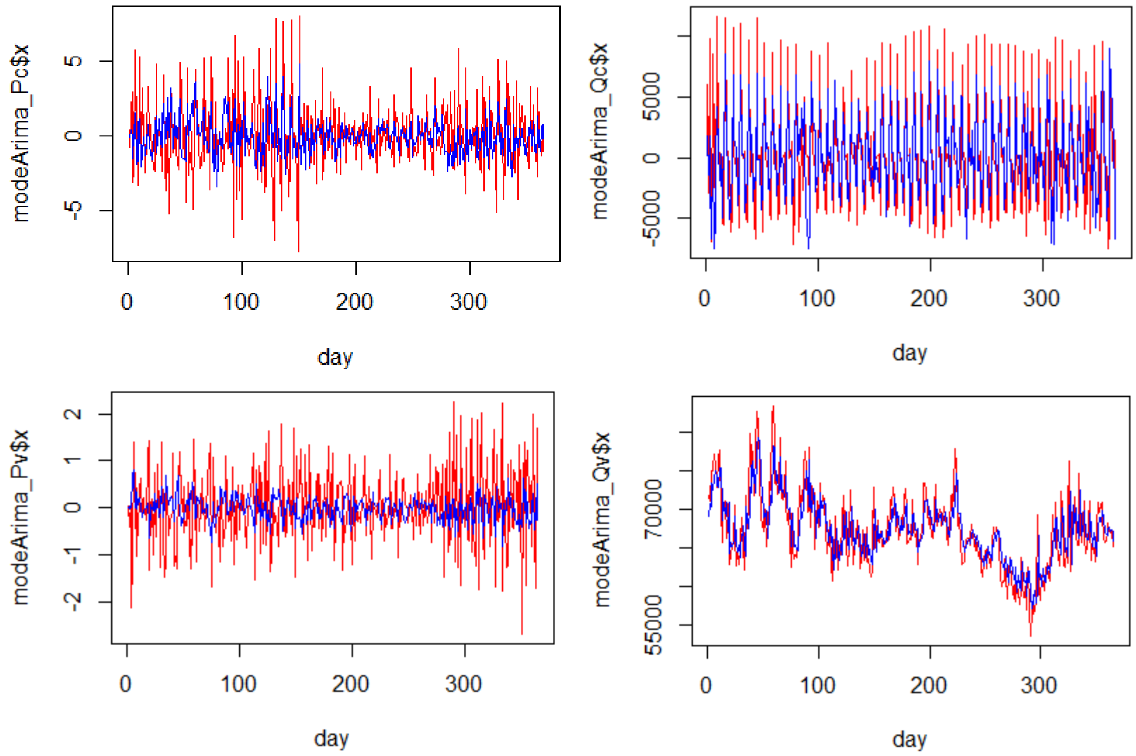
```
arima(x = diff(Pv), order = c(1, 0, 1))

Coefficients:
         ar1      ma1  intercept
      0.2770  -0.5979     0.0152
s.e.  0.1218   0.1008     0.0222

sigma^2 estimated as 0.5787:  log likelihood = -418.18,  aic = 844.37
```

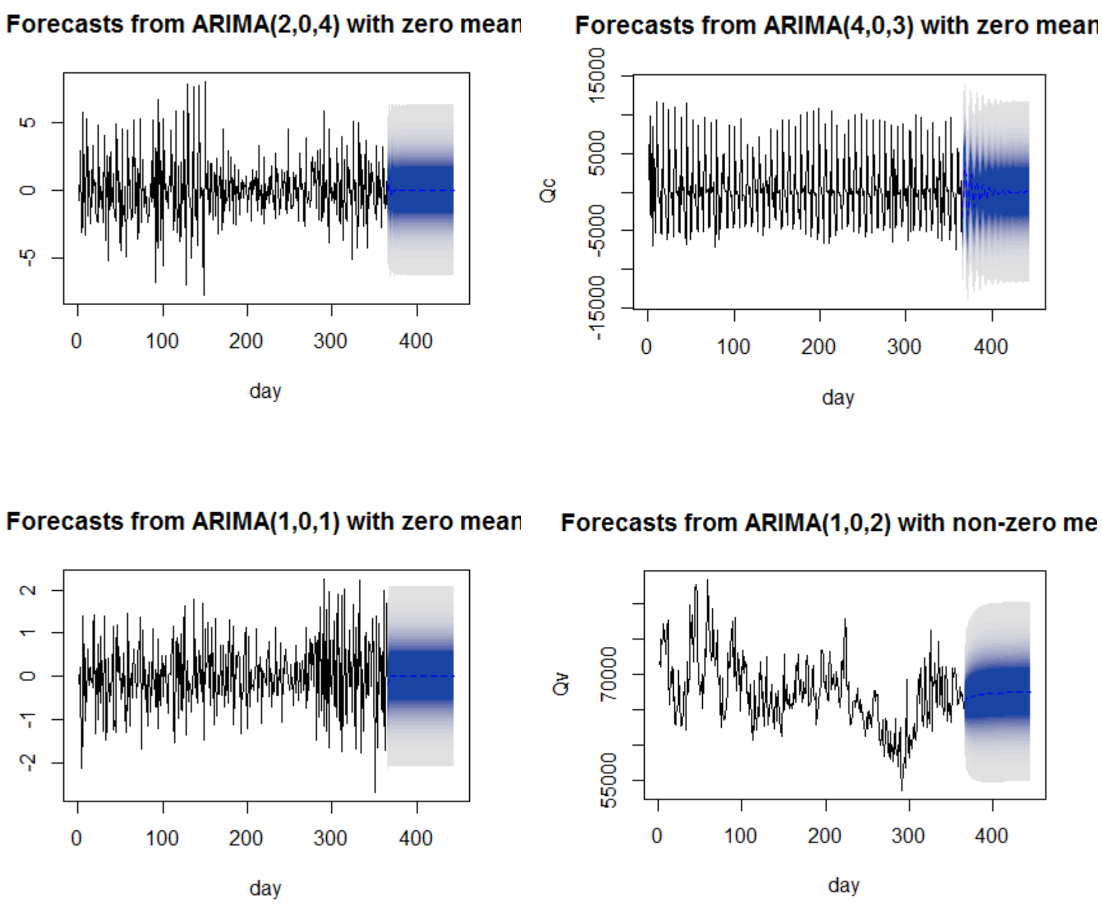
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.5027  0.6293  -0.1982  0.1633  -0.6119   66647.97
s.e.  0.1605  0.1250   0.1409  0.1423   0.1452    1258.63

sigma^2 estimated as 8962700:  log likelihood = -3449.53,  aic = 6913.06
```

H11 → (10:00am-10:59am)




```
data:  Pc
Dickey-Fuller = -2.3149, Lag order = 7, p-value = 0.4441
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.8097, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -3.1247, Lag order = 7, p-value = 0.1022
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -8.3377, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -1.9656, Lag order = 7, p-value = 0.5915
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.2639, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.3138, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.6368, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```


modeArima_Pc$x
modeArima_Qc$x
modeArima_Pv$x
modeArima_Qv$x
day


Forecasts from ARIMA(2,0,4) with zero mean
Forecasts from ARIMA(4,0,3) with zero mean
Forecasts from ARIMA(1,0,1) with zero mean
Forecasts from ARIMA(1,0,2) with non-zero me
Pc
Qc
Pv
Qv
day

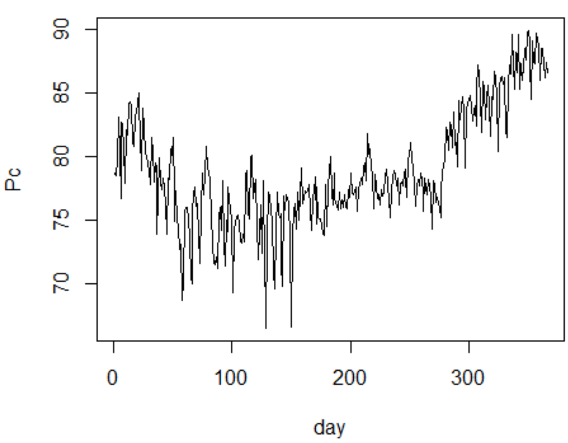
```
arima(x = diff(Pc), order = c(2, 0, 4))

Coefficients:
         ar1      ar2      ma1     ma2      ma3      ma4  intercept
      0.1736  -0.6592  -0.6120  0.5076  -0.1927  -0.3710     0.0225
s.e.  0.1290   0.0897   0.1227  0.1076   0.0706   0.0487     0.0248

sigma^2 estimated as 4.36:  log likelihood = -787.19,  aic = 1590.39
```

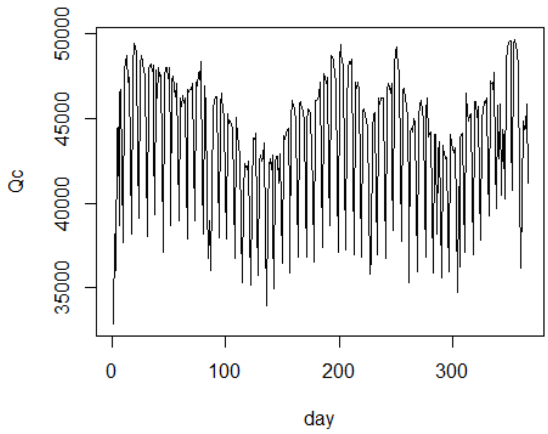
```
arima(x = diff(Qc), order = c(4, 0, 3))

Coefficients:
         ar1     ar2      ar3      ar4      ma1      ma2     ma3  intercept
      0.0261  0.0566  -0.4893  -0.3981  -0.5632  -0.5236  0.7082    14.6834
s.e.  0.0590  0.0543   0.0504   0.0581   0.0468   0.0599  0.0395    57.1760

sigma^2 estimated as 10017180:  log likelihood = -3461.61,  aic = 6941.22
```

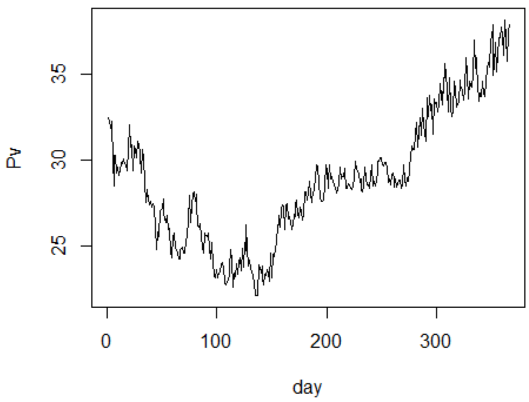
```
arima(x = diff(Pv), order = c(1, 0, 1))

Coefficients:
         ar1      ma1  intercept
      0.2678  -0.5937     0.0156
s.e.  0.1222   0.1012     0.0223

sigma^2 estimated as 0.5879:  log likelihood = -421.05,  aic = 850.09
```

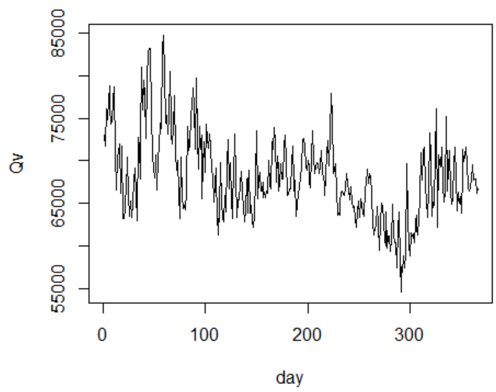
```
arima(x = Qv, order = c(1, 0, 2))

Coefficients:
         ar1      ma1      ma2  intercept
      0.9389  -0.2534  -0.2683  67481.506
s.e.  0.0255   0.0603   0.0641   1194.401

sigma^2 estimated as 9112207:  log likelihood = -3452.49,  aic = 6914.98
```

H12 → (11:00am-11:59am)

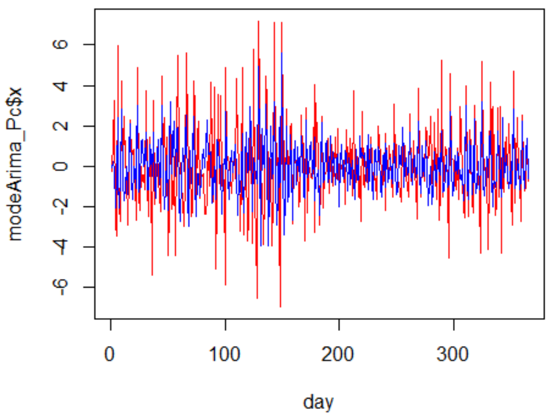


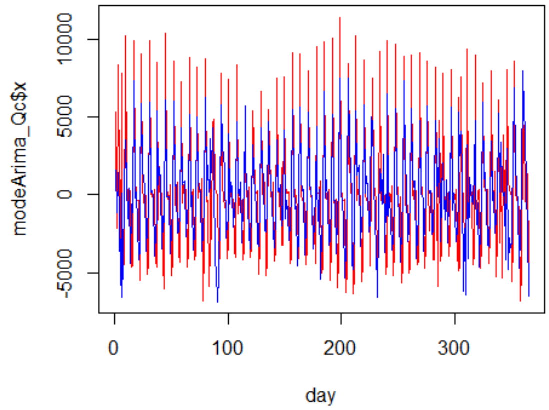


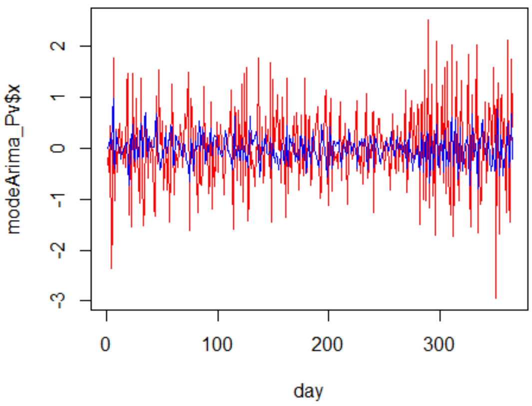


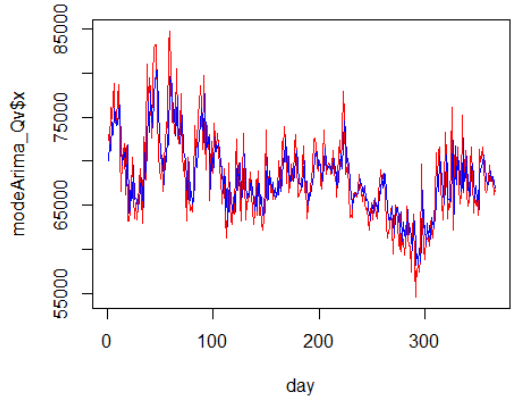



```
data:  Pc
Dickey-Fuller = -2.4335, Lag order = 7, p-value = 0.394
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.857, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -3.1508, Lag order = 7, p-value = 0.09648
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -8.1795, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -2.0088, Lag order = 7, p-value = 0.5732
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.3006, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.37, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.3129, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

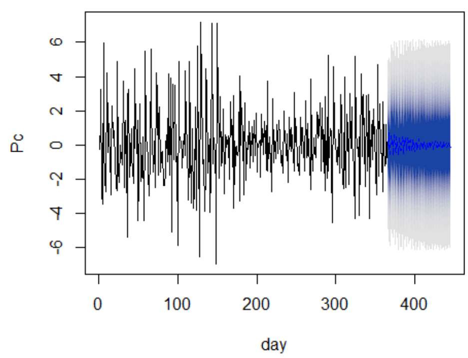




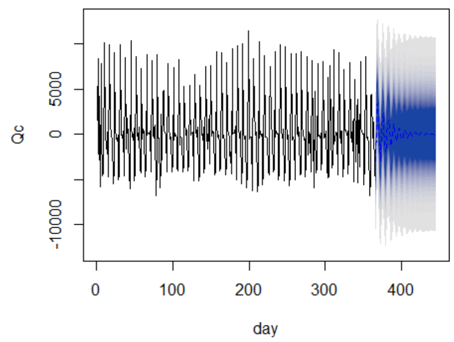




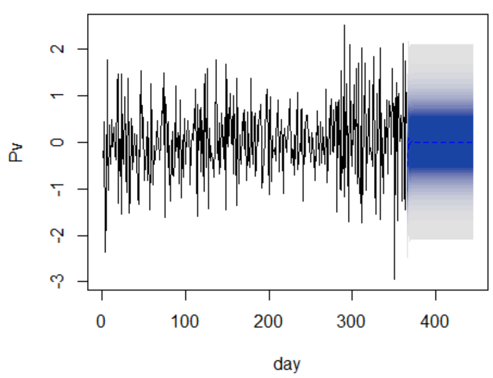
Forecasts from ARIMA(2,0,3) with zero mean



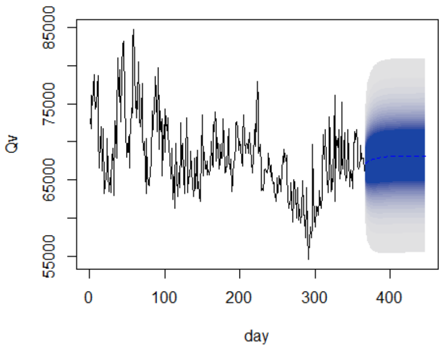
Forecasts from ARIMA(4,0,3) with zero mean



Forecasts from ARIMA(2,0,0) with zero mean



Forecasts from ARIMA(3,0,2) with non-zero mean



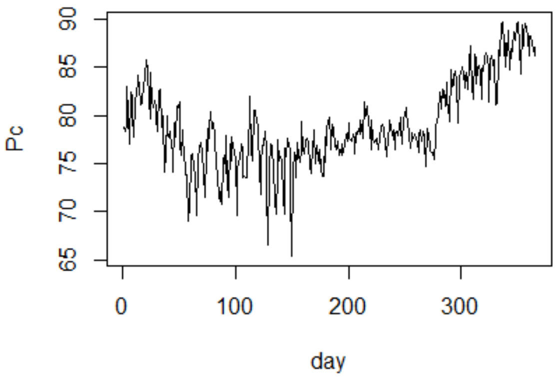
```
arima(x = diff(Pc), order = c(2, 0, 3))

Coefficients:
          ar1      ar2     ma1     ma2      ma3  intercept
      -0.4711  -0.9602  0.0647  0.6566  -0.5233     0.0215
s.e.   0.0181   0.0155  0.0801  0.0542   0.0810     0.0492

sigma^2 estimated as 3.616:  log likelihood = -754.37,  aic = 1522.74
```

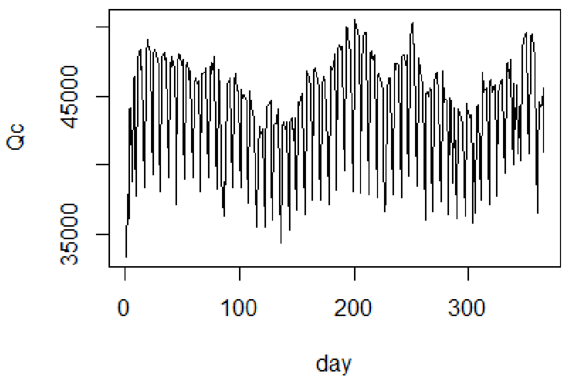
```
arima(x = diff(Qc), order = c(4, 0, 3))

Coefficients:
         ar1     ar2      ar3      ar4      ma1      ma2     ma3  intercept
      0.0291  0.0533  -0.4999  -0.4049  -0.5341  -0.5127  0.7167    14.0188
s.e.  0.0581  0.0546   0.0507   0.0608   0.0480   0.0675  0.0394    56.4486

sigma^2 estimated as 8568154:  log likelihood = -3433.09,  aic = 6884.18
```

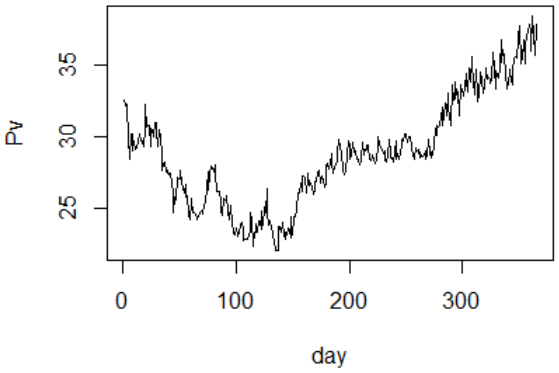
```
arima(x = diff(Pv), order = c(2, 0, 0))

Coefficients:
          ar1      ar2  intercept
      -0.3151  -0.2234     0.0142
s.e.   0.0511   0.0513     0.0262

sigma^2 estimated as 0.5906:  log likelihood = -421.88,  aic = 851.76
```

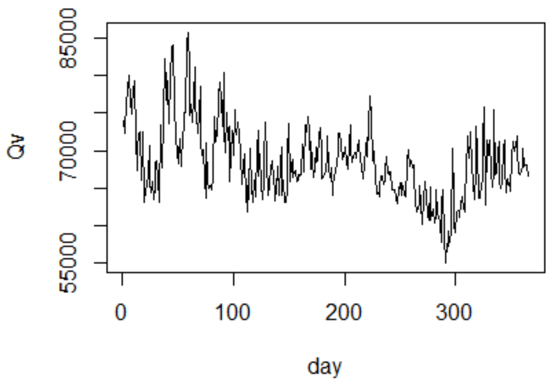
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.5390  0.4248  -0.0605  0.1337  -0.4217  68182.438
s.e.  0.1764  0.1978   0.1427  0.1658   0.1609   1122.633

sigma^2 estimated as 9023253:  log likelihood = -3450.71,  aic = 6915.42
```

H13 → (12:00pm-12:59pm)

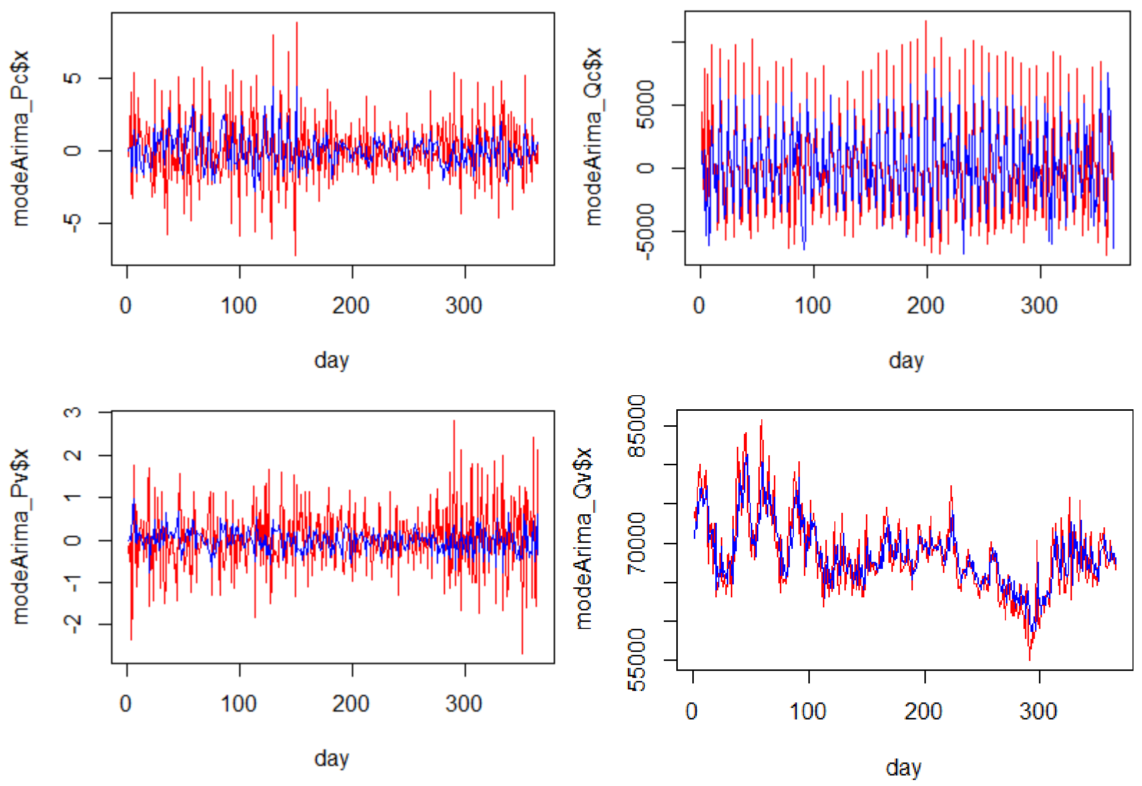


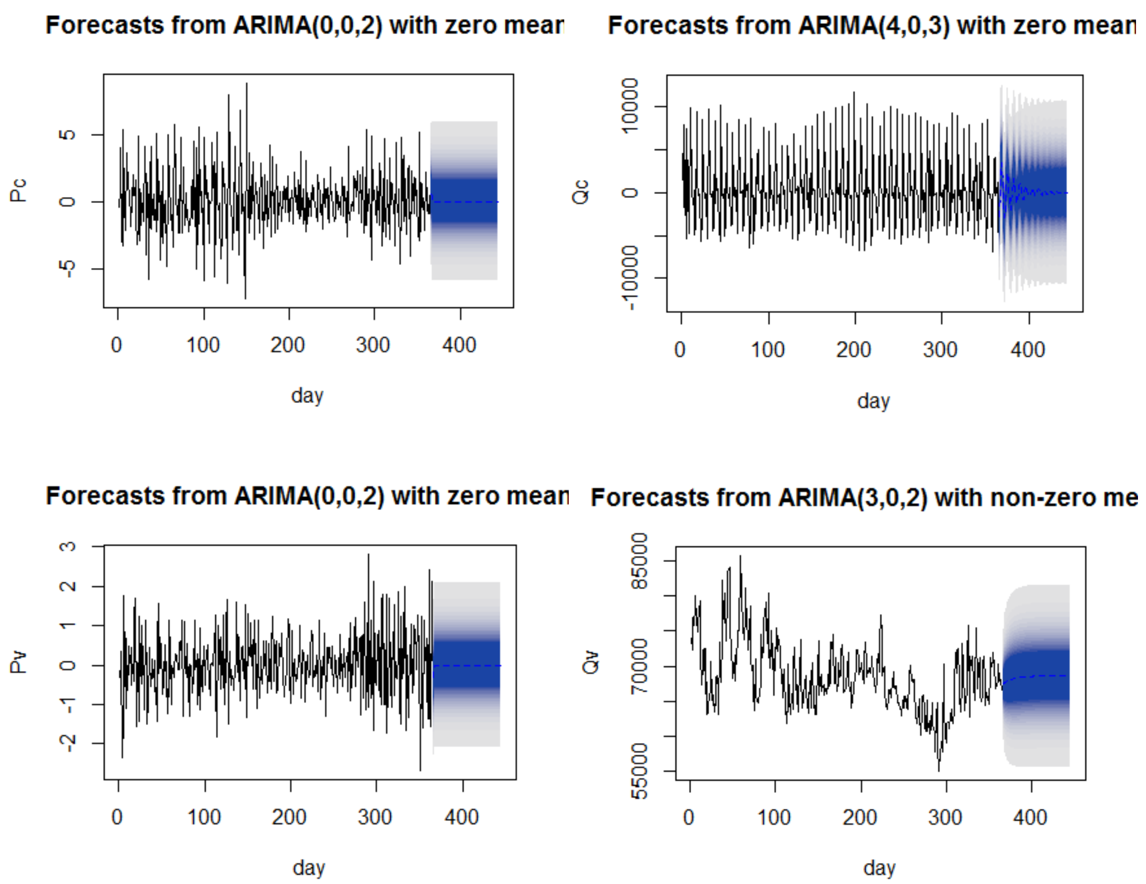







```
data:  Pc
Dickey-Fuller = -2.386, Lag order = 7, p-value = 0.414
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.5179, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -3.1388, Lag order = 7, p-value = 0.09851
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -8.1288, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -1.9943, Lag order = 7, p-value = 0.5794
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.5075, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.3999, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.1179, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```


modeArima_Pc$x
modeArima_Qc$x
modeArima_Pv$x
modeArima_Qv$x
day


Forecasts from ARIMA(0,0,2) with zero mear
Forecasts from ARIMA(4,0,3) with zero mean
Forecasts from ARIMA(0,0,2) with zero mean
Forecasts from ARIMA(3,0,2) with non-zero me
Pc
Qc
Pv
Qv
day

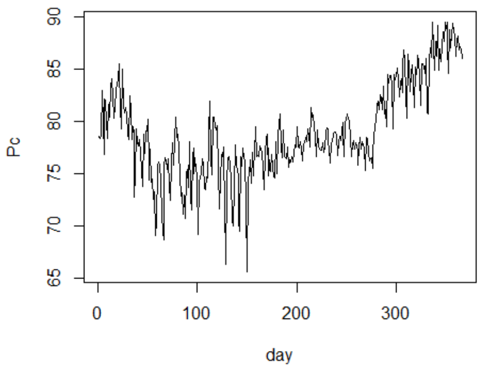
```
arima(x = diff(Pc), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.3949  -0.3479     0.0204
s.e.   0.0485   0.0485     0.0278

sigma^2 estimated as 4.15:  log likelihood = -777.99,  aic = 1563.99
```

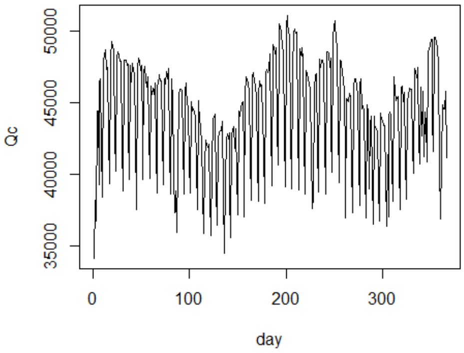
```
arima(x = diff(Qc), order = c(4, 0, 3))

Coefficients:
         ar1     ar2      ar3      ar4      ma1      ma2     ma3  intercept
      0.0478  0.0374  -0.4989  -0.3988  -0.5338  -0.5071  0.7171    13.4746
s.e.  0.0584  0.0564   0.0517   0.0617   0.0486   0.0717  0.0403    56.5278

sigma^2 estimated as 8339527:  log likelihood = -3428.18,  aic = 6874.35
```

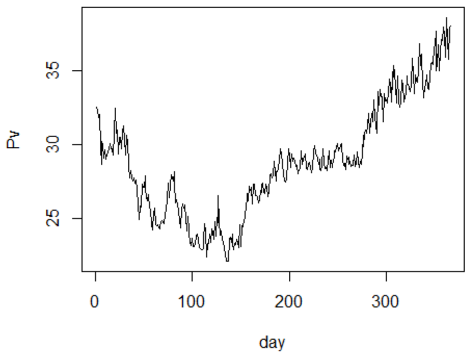
```
arima(x = diff(Pv), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.3293  -0.1083     0.0147
s.e.   0.0534   0.0553     0.0226

sigma^2 estimated as 0.5883:  log likelihood = -421.18,  aic = 850.35
```

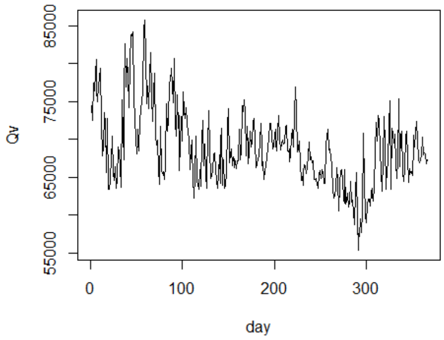
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.5496  0.3884  -0.0393  0.1333  -0.3867  68605.092
s.e.  0.1773  0.1861   0.1374  0.1678   0.1540   1131.377

sigma^2 estimated as 9106696:  log likelihood = -3452.4,  aic = 6918.8
```

H14 → (1:00pm-1:59pm)

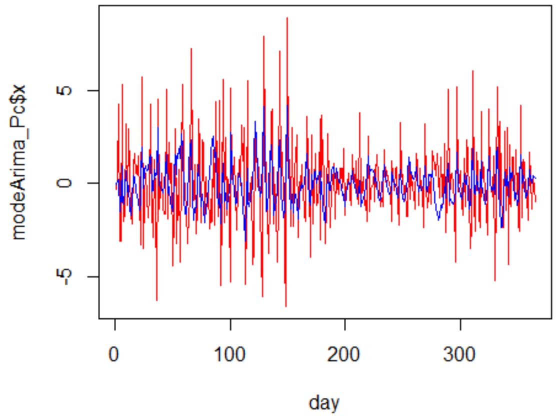


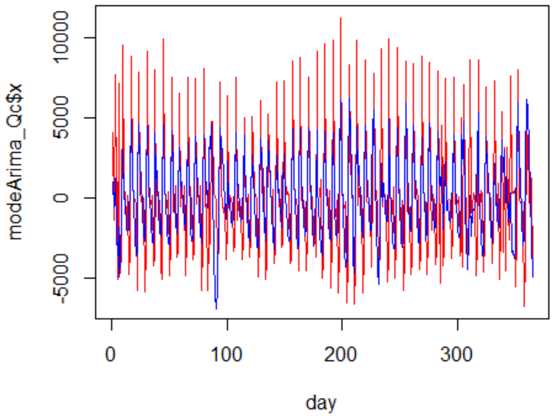


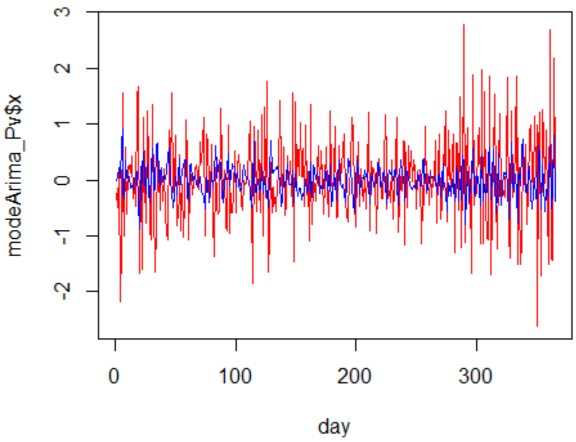


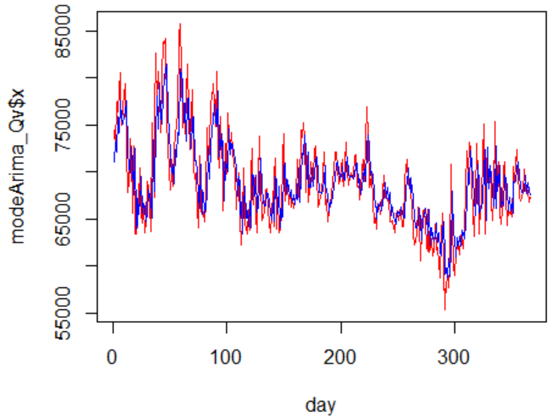



```
data:  Pc
Dickey-Fuller = -2.4361, Lag order = 7, p-value = 0.3929
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.3766, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -2.8722, Lag order = 7, p-value = 0.2088
alternative hypothesis: stationary


data:  diff(Qc)
Dickey-Fuller = -7.954, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.9261, Lag order = 7, p-value = 0.6081
alternative hypothesis: stationary


data:  diff(Pv)
Dickey-Fuller = -8.5296, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.5089, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  diff(Qv)
Dickey-Fuller = -8.0993, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

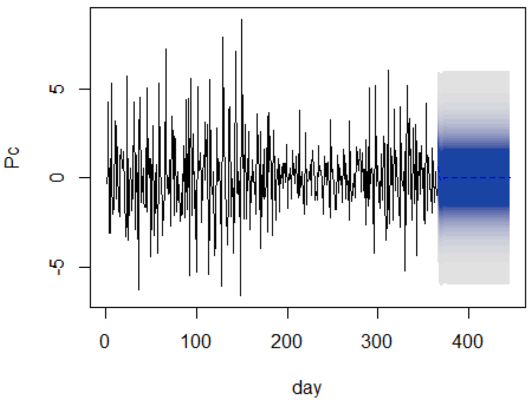




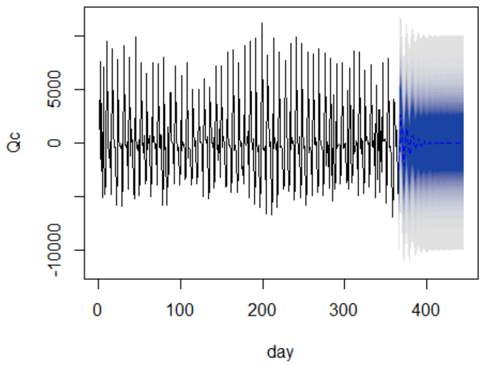




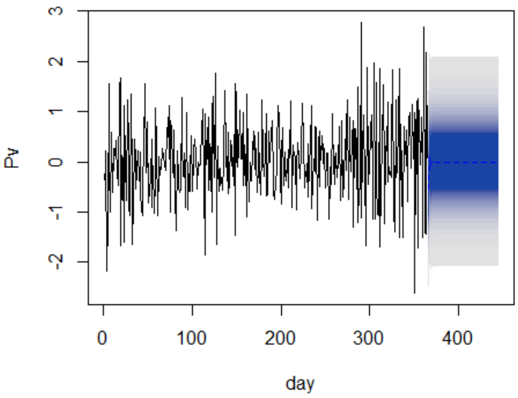
Forecasts from ARIMA(2,0,2) with zero mean



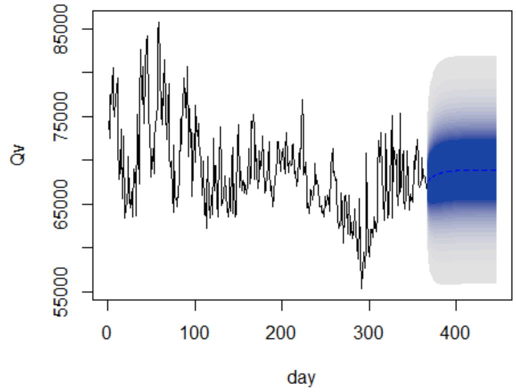
Forecasts from ARIMA(3,0,2) with zero mean



Forecasts from ARIMA(2,0,0) with zero mean



Forecasts from ARIMA(3,0,2) with non-zero mean



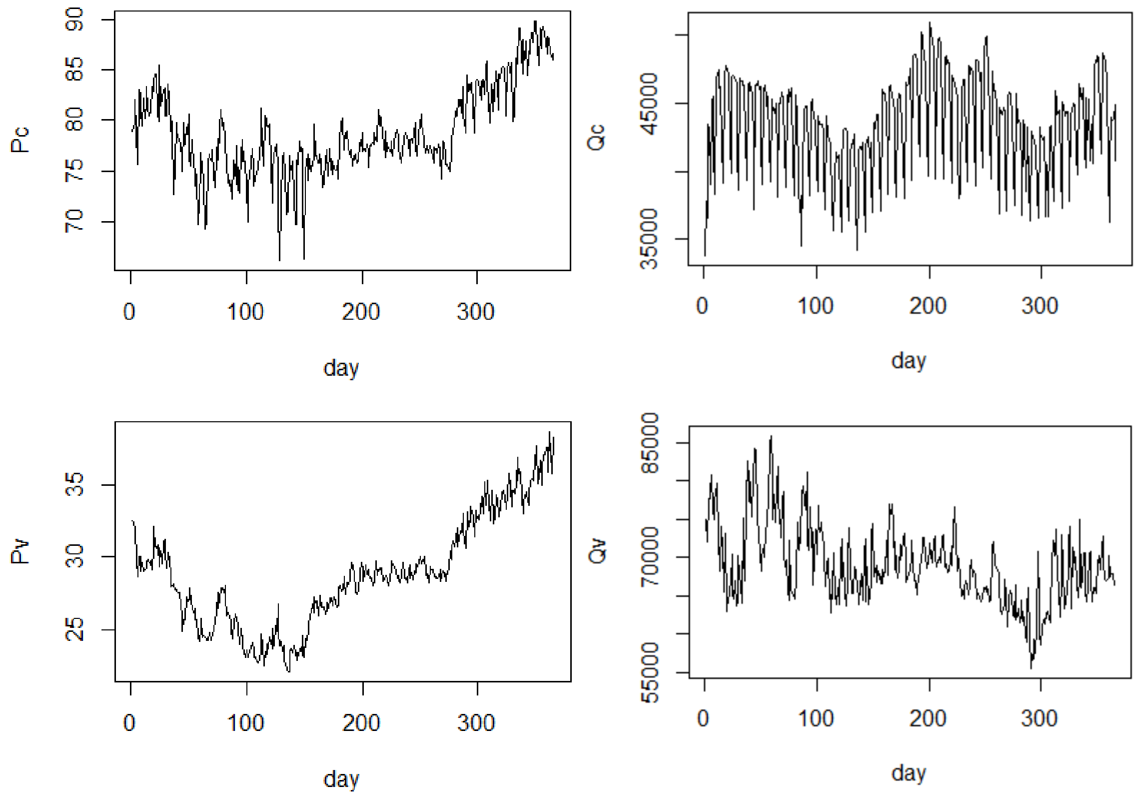
```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      0.9261  -0.3949  -1.3372  0.4908     0.0208
s.e.  0.1530   0.0983   0.1495  0.1392     0.0352

sigma^2 estimated as 4.182:  log likelihood = -779.37,  aic = 1570.73
```

```
arima(x = diff(Qc), order = c(3, 0, 2))

Coefficients:
         ar1      ar2      ar3      ma1     ma2  intercept
      0.9292  -0.5731  -0.1860  -1.4967  0.7919    13.2495
s.e.  0.0626   0.0674   0.0634   0.0408  0.0349    54.7612

sigma^2 estimated as 8614906:  log likelihood = -3433.58,  aic = 6881.15
```

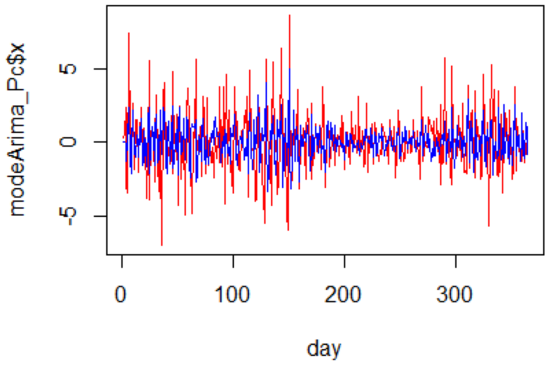
```
arima(x = diff(Pv), order = c(2, 0, 0))

Coefficients:
          ar1      ar2  intercept
      -0.3262  -0.2333     0.0146
s.e.   0.0509   0.0514     0.0256

sigma^2 estimated as 0.5783:  log likelihood = -418.04,  aic = 844.09
```

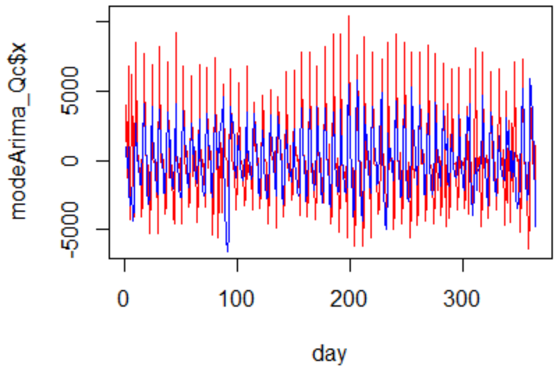
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.5414  0.3668  -0.0175  0.1650  -0.3724  68885.067
s.e.  0.1731  0.1600   0.1336  0.1643   0.1490   1115.112

sigma^2 estimated as 9116547:  log likelihood = -3452.61,  aic = 6919.22
```

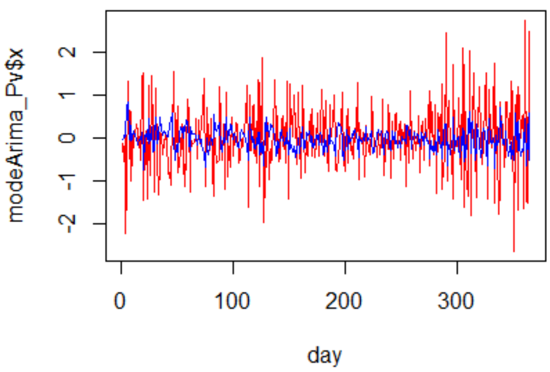
H15 → (2:00pm-2:59pm)

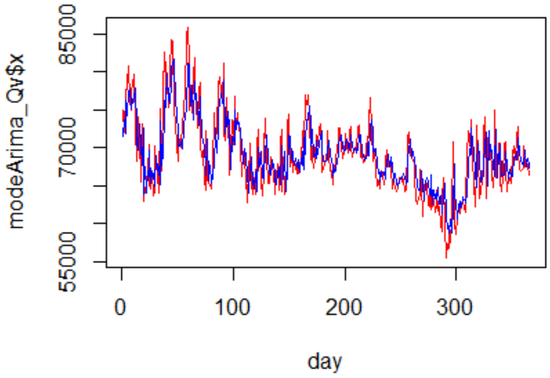


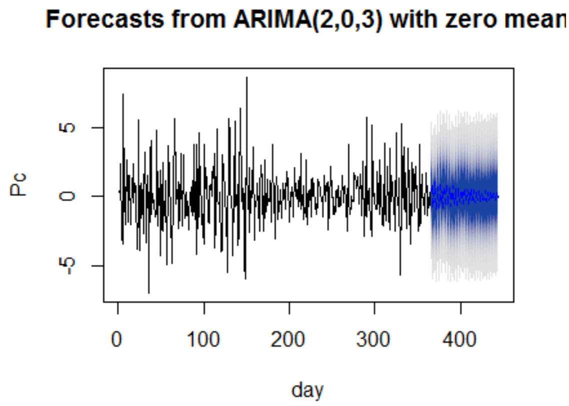

```
data:  Pc
Dickey-Fuller = -2.3553, Lag order = 7, p-value = 0.427
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.7408, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -2.7037, Lag order = 7, p-value = 0.2799
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.8374, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -1.9285, Lag order = 7, p-value = 0.6071
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.4154, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.5504, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.0323, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

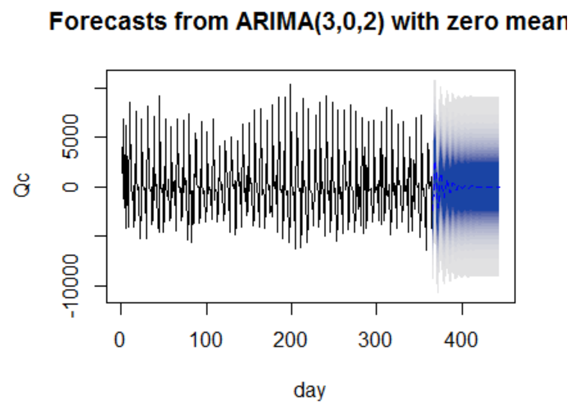

modeArima_Pc$x
day

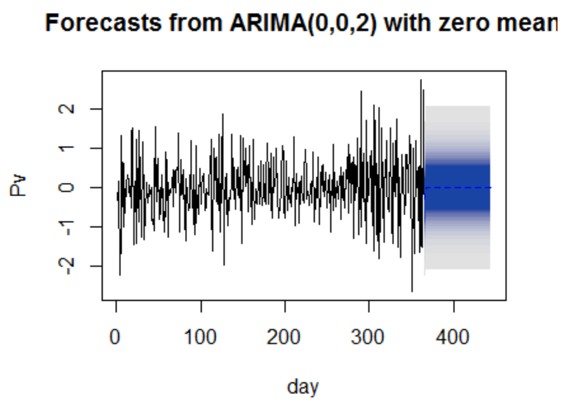

modeArima_Qc$x
day

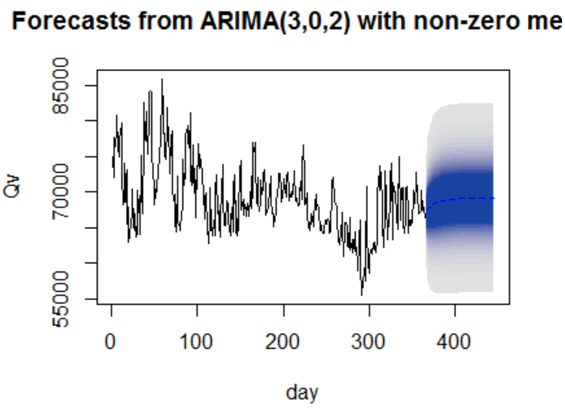

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(2,0,3) with zero mean
Pc
day


Forecasts from ARIMA(3,0,2) with zero mean
Qc
day


Forecasts from ARIMA(0,0,2) with zero mean
Pv
day


Forecasts from ARIMA(3,0,2) with non-zero me
Qv
day

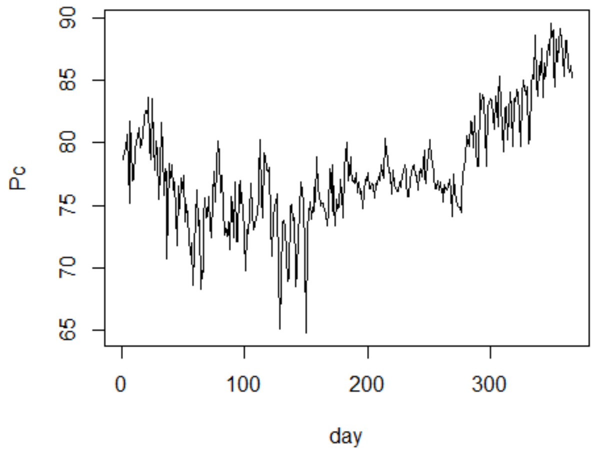
```
arima(x = diff(Pc), order = c(2, 0, 3))

Coefficients:
          ar1      ar2     ma1     ma2      ma3  intercept
      -0.4653  -0.9682  0.1202  0.6983  -0.4308     0.0203
s.e.   0.0213   0.0159  0.0910  0.0587   0.1012     0.0568

sigma^2 estimated as 3.601:  log likelihood = -753.02,  aic = 1520.04
```

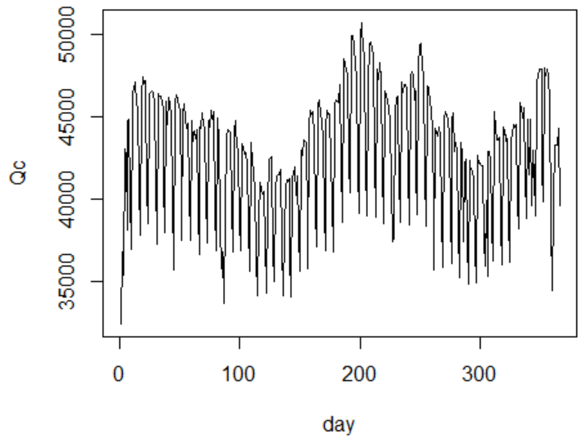
```
arima(x = diff(Qc), order = c(3, 0, 2))

Coefficients:
         ar1      ar2      ar3      ma1     ma2  intercept
      0.9438  -0.5843  -0.1835  -1.4872  0.7914    13.2918
s.e.  0.0635   0.0682   0.0639   0.0425  0.0347    52.2613

sigma^2 estimated as 7287416:  log likelihood = -3403.01,  aic = 6820.01
```

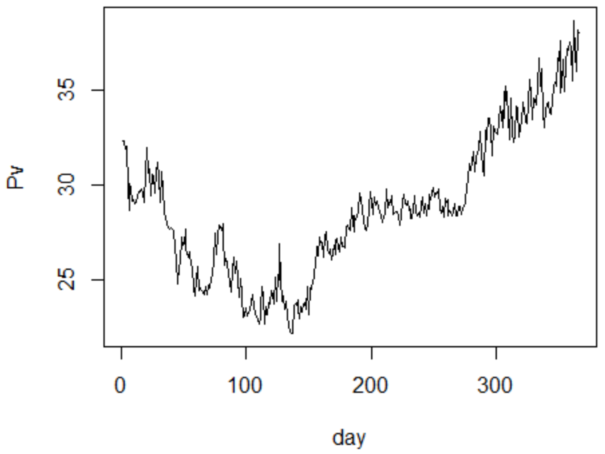
```
arima(x = diff(Pv), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.3324  -0.0910     0.0152
s.e.   0.0534   0.0555     0.0230

sigma^2 estimated as 0.5769:  log likelihood = -417.6,  aic = 843.2
```

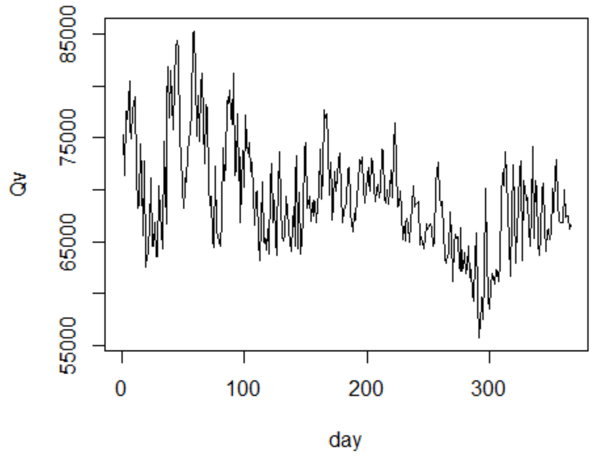
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.5499  0.3708  -0.0283  0.1587  -0.3705  69118.231
s.e.  0.1782  0.1668   0.1366  0.1691   0.1518   1135.058

sigma^2 estimated as 9263825:  log likelihood = -3455.54,  aic = 6925.09
```

H16 → (3:00pm-3:59pm)

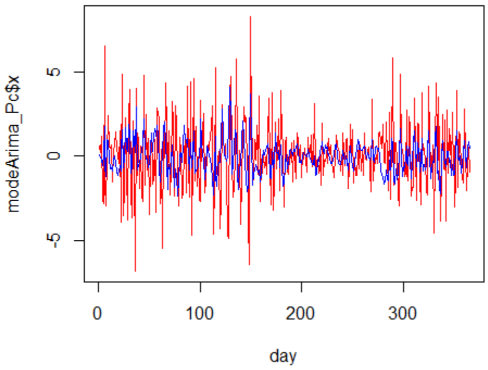


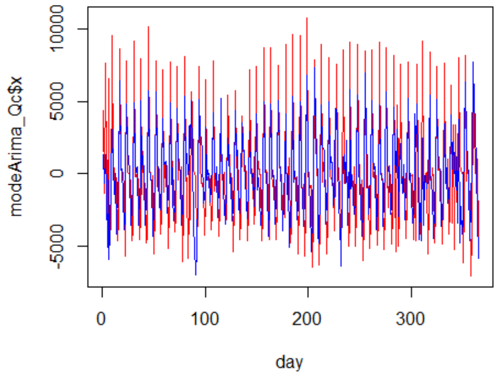


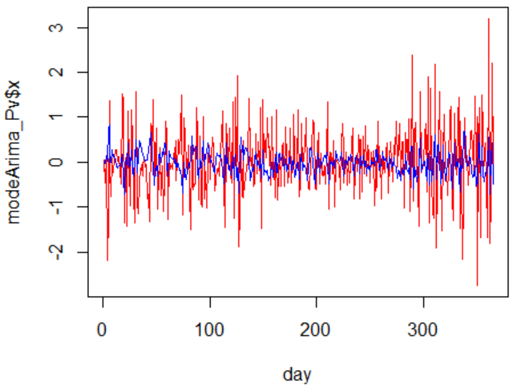


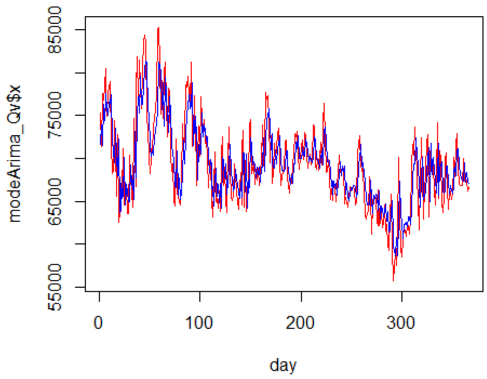



```
data:  Pc
Dickey-Fuller = -2.289, Lag order = 7, p-value = 0.455
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.9567, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -2.5225, Lag order = 7, p-value = 0.3564
alternative hypothesis: stationary
data:  diff(Qc)
Dickey-Fuller = -8.1299, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.9052, Lag order = 7, p-value = 0.6169
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.2359, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.5413, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -7.9718, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

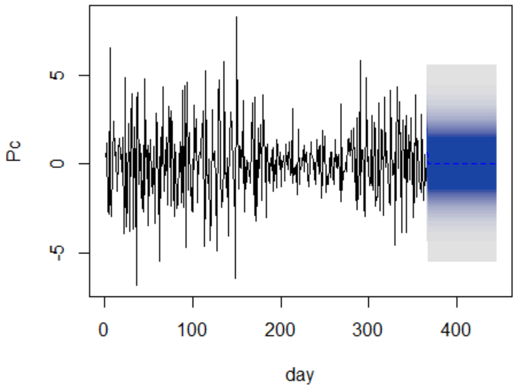




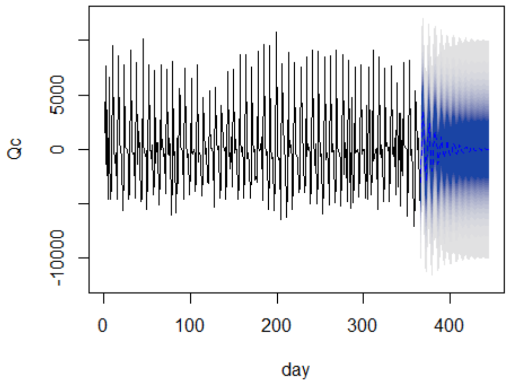




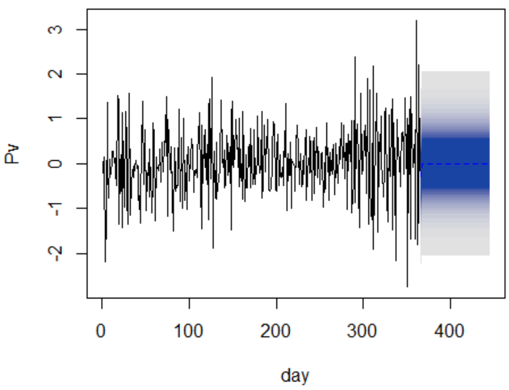
Forecasts from ARIMA(0,0,2) with zero mean



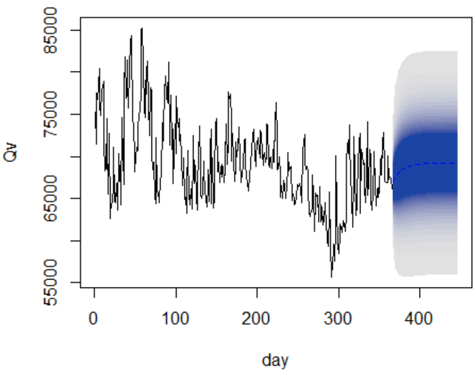
Forecasts from ARIMA(4,0,3) with zero mean



Forecasts from ARIMA(0,0,2) with zero mean



Forecasts from ARIMA(3,0,2) with non-zero mean



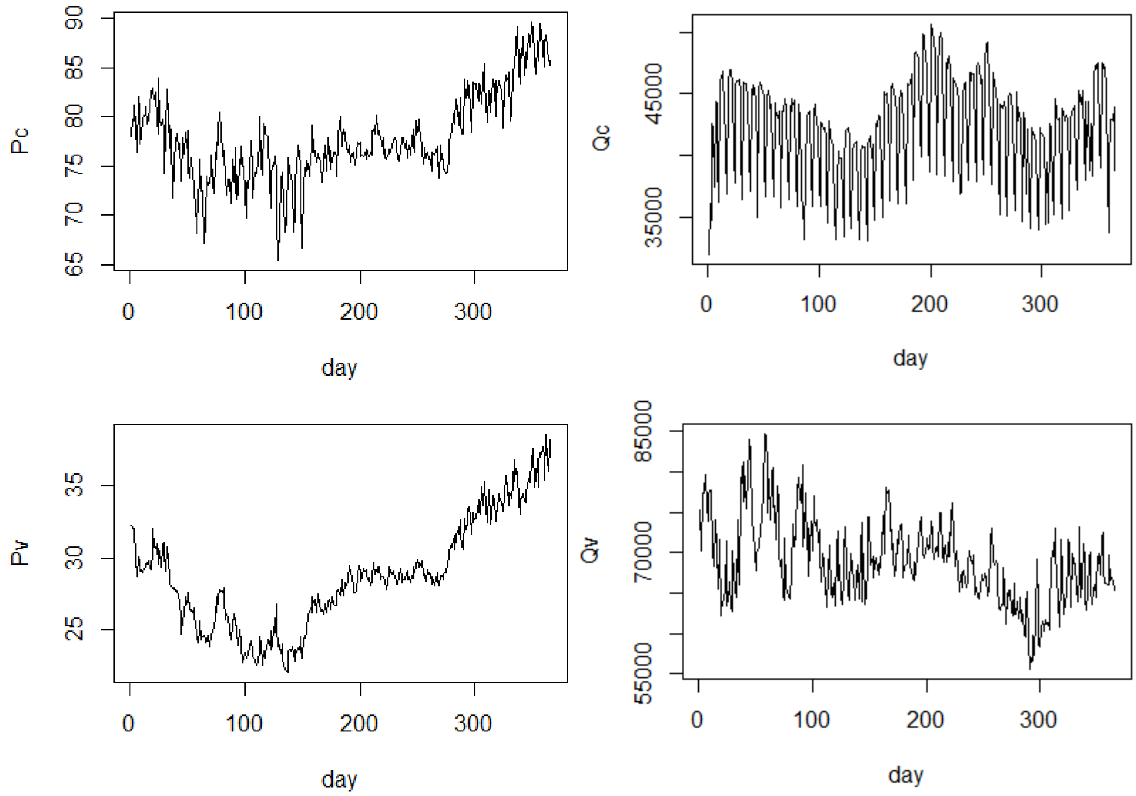
```
arima(x = diff(Pc), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.3561  -0.3532     0.0203
s.e.   0.0483   0.0477     0.0294

sigma^2 estimated as 3.663:  log likelihood = -755.15,  aic = 1518.3
```

```
arima(x = diff(Qc), order = c(4, 0, 3))

Coefficients:
         ar1     ar2      ar3      ar4      ma1      ma2     ma3  intercept
      0.0774  0.0310  -0.4991  -0.3826  -0.5553  -0.4968  0.6979    12.9430
s.e.  0.0611  0.0606   0.0541   0.0611   0.0519   0.0722  0.0417    51.6041

sigma^2 estimated as 7293122:  log likelihood = -3403.68,  aic = 6825.36
```

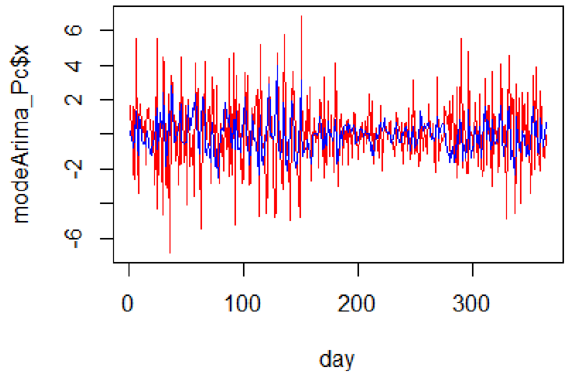
```
arima(x = diff(Pv), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.3321  -0.0959     0.0156
s.e.   0.0539   0.0561     0.0226

sigma^2 estimated as 0.568:  log likelihood = -414.75,  aic = 837.51
```

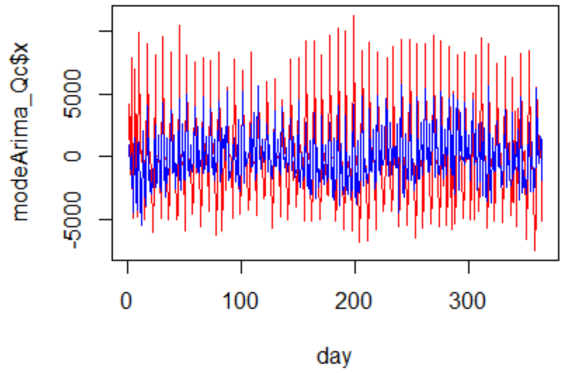
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.5422  0.3642  -0.0156  0.1616  -0.3590  69217.661
s.e.  0.1782  0.1634   0.1356  0.1697   0.1509   1141.016

sigma^2 estimated as 9308871:  log likelihood = -3456.43,  aic = 6926.87
```

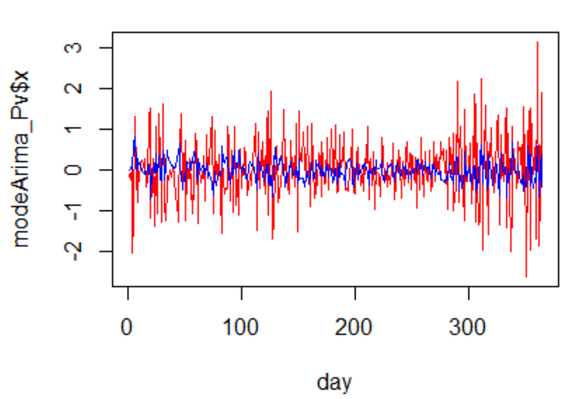
H17 → (4:00pm-4:59pm)

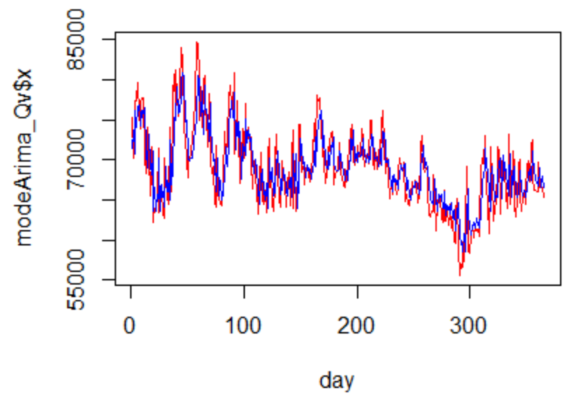


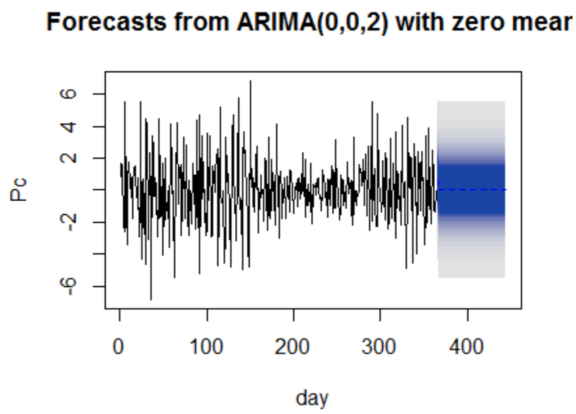

```
data:  Pc
Dickey-Fuller = -2.4061, Lag order = 7, p-value = 0.4056
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.6287, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -2.4108, Lag order = 7, p-value = 0.4036
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -8.1447, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -1.9059, Lag order = 7, p-value = 0.6167
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.135, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.5026, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -7.9376, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

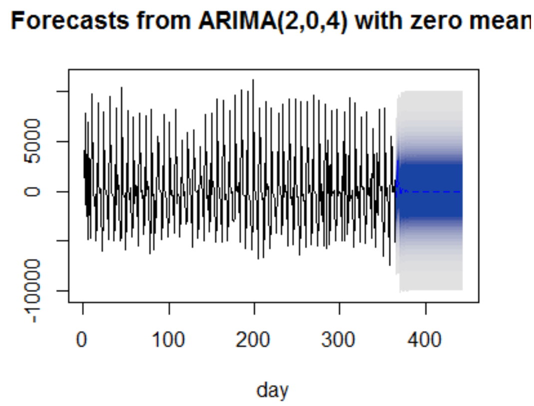

modeArima_Pc$x
day

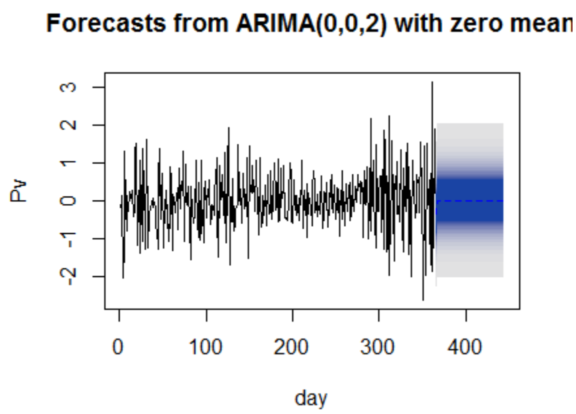

modeArima_Qc$x
day

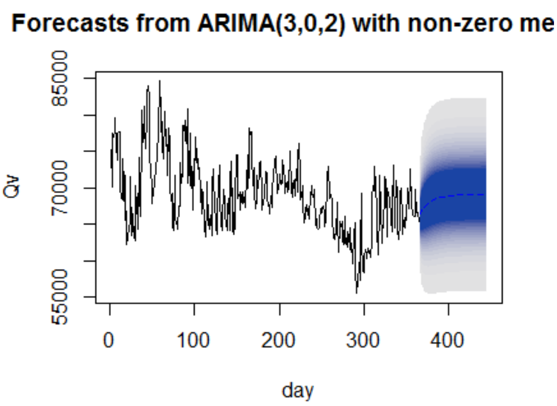

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(0,0,2) with zero mear
Pc
day


Forecasts from ARIMA(2,0,4) with zero mean
Qc
day


Forecasts from ARIMA(0,0,2) with zero mean
Pv
day


Forecasts from ARIMA(3,0,2) with non-zero me
Qv
day

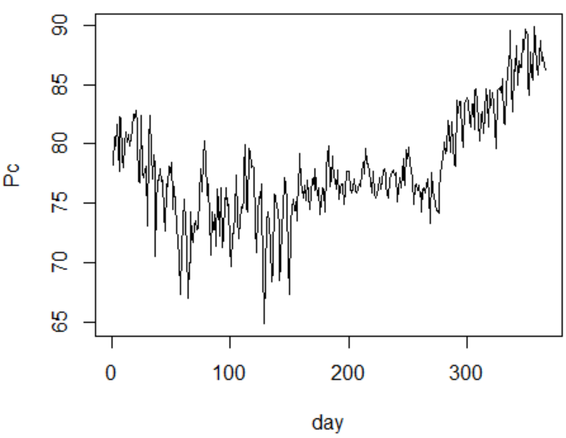
```
arima(x = diff(Pc), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.3697  -0.3289     0.0196
s.e.   0.0477   0.0466     0.0306

sigma^2 estimated as 3.692:  log likelihood = -756.56,  aic = 1521.13
```

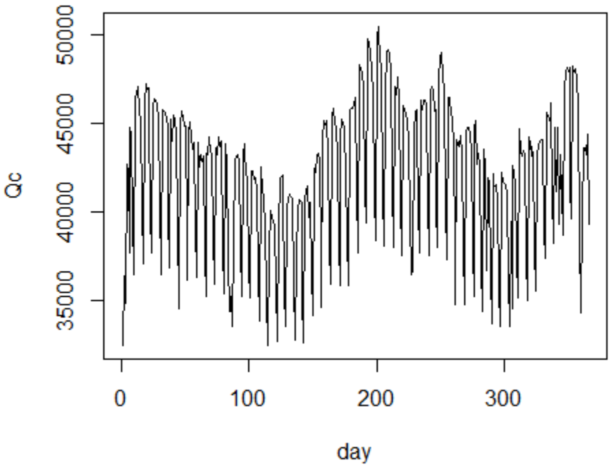
```
arima(x = diff(Qc), order = c(2, 0, 4))

Coefficients:
         ar1      ar2      ma1     ma2     ma3      ma4  intercept
      0.1937  -0.5083  -0.4996  0.1855  0.1527  -0.6987     3.4486
s.e.  0.0869   0.0648   0.0772  0.0792  0.0683   0.0476    17.9404

sigma^2 estimated as 9262598:  log likelihood = -3447.04,  aic = 6910.08
```

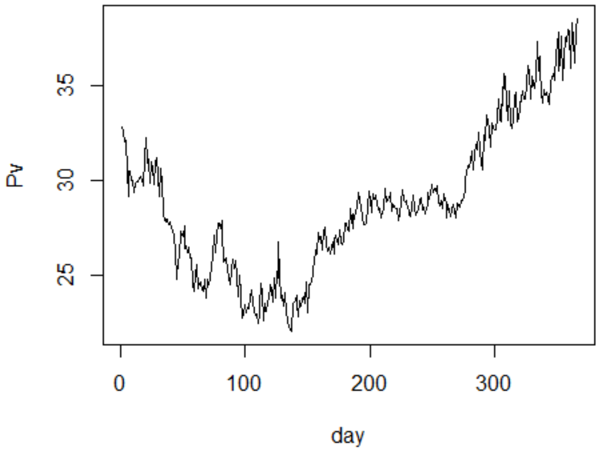
```
arima(x = diff(Pv), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.3219  -0.1047     0.0156
s.e.   0.0540   0.0558     0.0224

sigma^2 estimated as 0.5526:  log likelihood = -409.74,  aic = 827.48
```

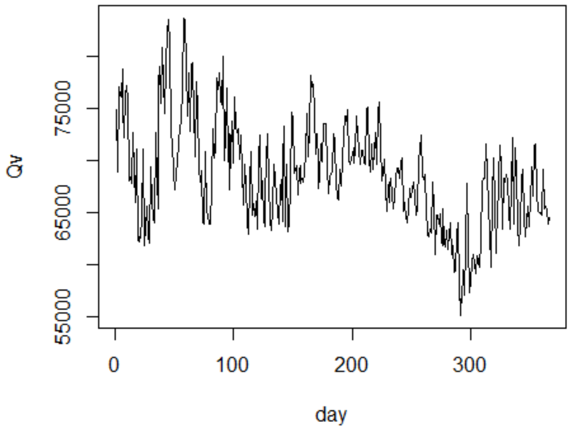
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2      ar3     ma1      ma2  intercept
      0.5180  0.3771  -0.0057  0.1728  -0.3646   69038.69
s.e.  0.1719  0.1545   0.1314  0.1635   0.1462    1138.13

sigma^2 estimated as 9380355:  log likelihood = -3457.83,  aic = 6929.66
```

H18 → (5:00pm-5:59pm)

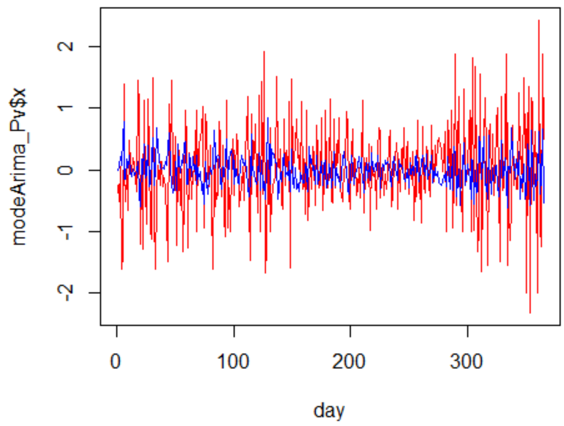


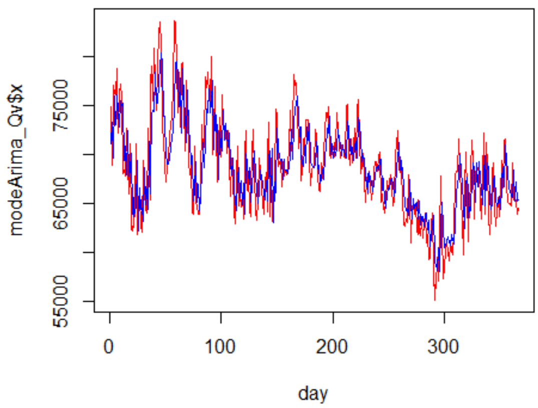


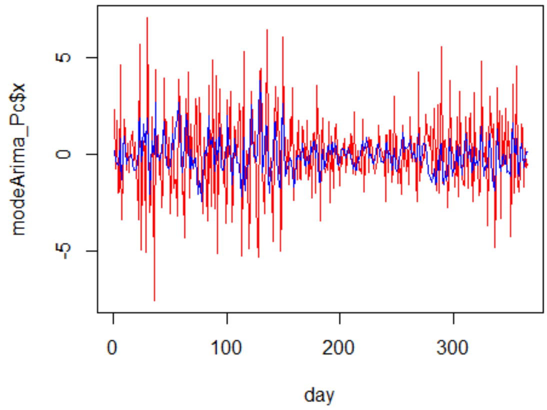


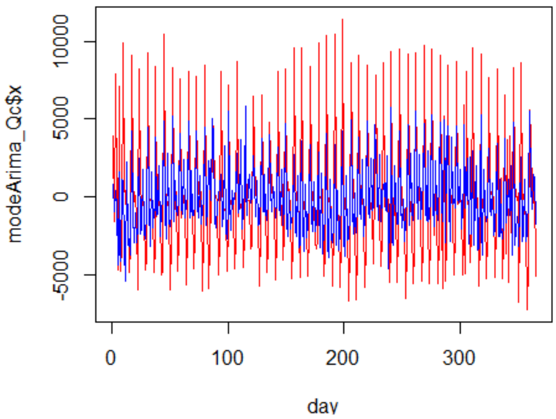


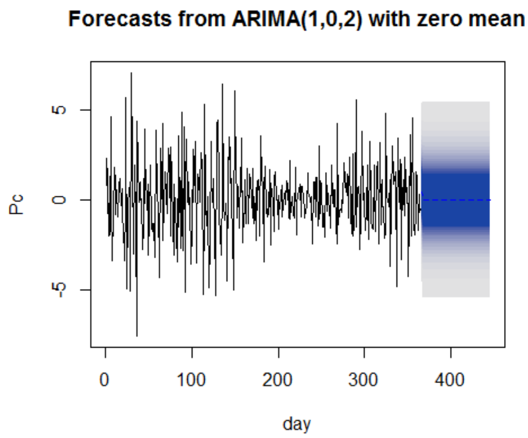

```
data:  Pc
Dickey-Fuller = -2.6436, Lag order = 7, p-value = 0.3053
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.8857, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -2.4522, Lag order = 7, p-value = 0.3861
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -8.0495, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.9287, Lag order = 7, p-value = 0.607
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -7.9198, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.4161, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -7.9488, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

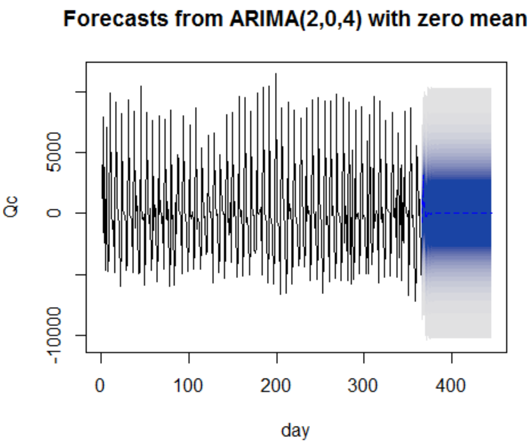

modeArima_Pv$x
day
-2
-1
0
1
2
0
100
200
300

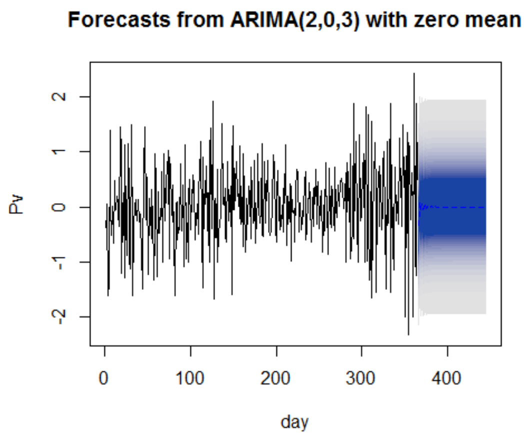

modeArima_Qv$x
day
55000
65000
75000
0
100
200
300

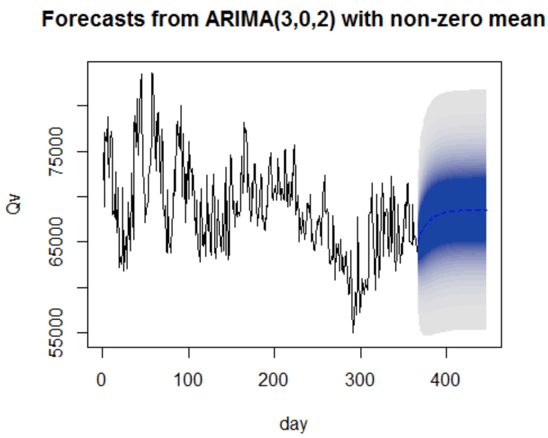

modeArima_Pc$x
day
-5
0
5
0
100
200
300


modeArima_Qc$x
day
-5000
0
5000
10000
0
100
200
300


Forecasts from ARIMA(1,0,2) with zero mean
Pc
day
-5
0
5
0
100
200
300
400

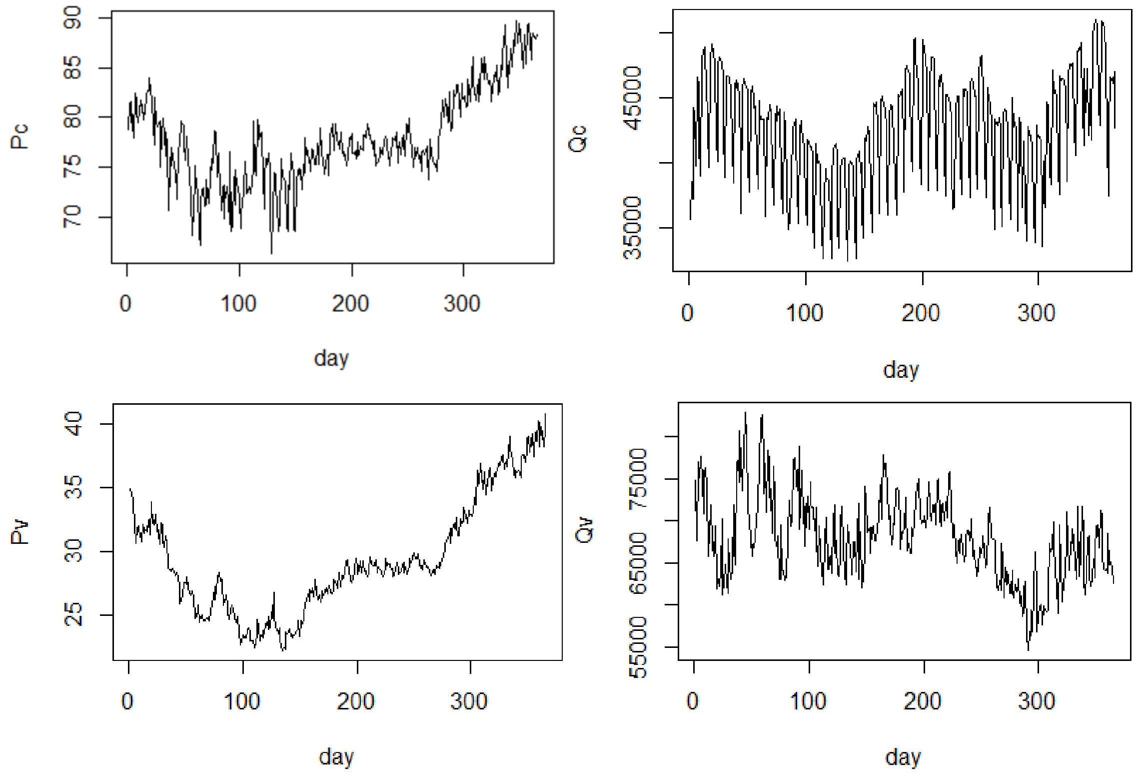

Forecasts from ARIMA(2,0,4) with zero mean
Qc
day
-10000
0
5000
0
100
200
300
400


Forecasts from ARIMA(2,0,3) with zero mean
Pv
day
-2
-1
0
1
2
0
100
200
300
400

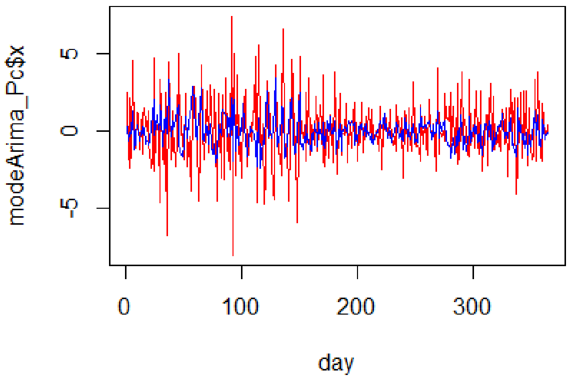

Forecasts from ARIMA(3,0,2) with non-zero mean
Qv
day
55000
65000
75000
0
100
200
300
400

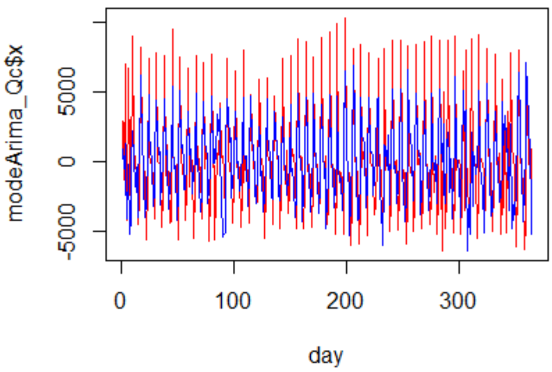
```
arima(x = diff(Pc), order = c(1, 0, 2))

Coefficients:
         ar1      ma1      ma2  intercept
      0.1612  -0.4682  -0.2974     0.0204
s.e.  0.1250   0.1181   0.0770     0.0282

sigma^2 estimated as 3.628:  log likelihood = -753.39,  aic = 1516.79



arima(x = diff(Qc), order = c(2, 0, 4))

Coefficients:
         ar1      ar2      ma1     ma2     ma3      ma4  intercept
      0.1796  -0.5010  -0.4795  0.1677  0.1580  -0.7063     4.4440
s.e.  0.0867   0.0643   0.0752  0.0746  0.0652   0.0453    18.1688

sigma^2 estimated as 9590329:  log likelihood = -3453.4,  aic = 6922.8



arima(x = diff(Pv), order = c(2, 0, 3))

Coefficients:
         ar1     ar2      ma1     ma2    ma3  intercept
      0.0498  0.7125  -0.3685  -0.794  0.313     0.0152
s.e.     NaN     NaN      NaN     NaN    NaN     0.0234

sigma^2 estimated as 0.4971:  log likelihood = -390.48,  aic = 794.95



arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2     ar3     ma1      ma2  intercept
      0.5052  0.3747  0.0107  0.1947  -0.3721  68533.554
s.e.  0.1641  0.1429  0.1288  0.1560   0.1433   1156.172

sigma^2 estimated as 9172005:  log likelihood = -3453.75,  aic = 6921.5
```

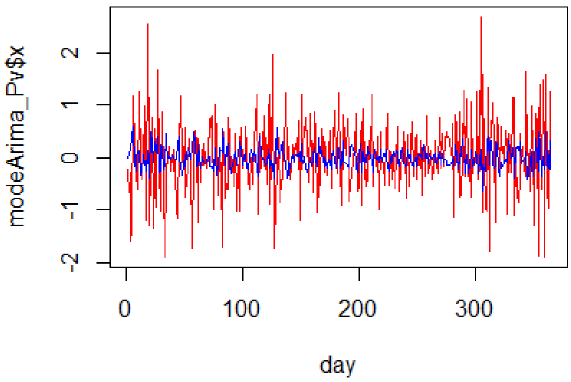
H19 → (6:00pm-6:59pm)

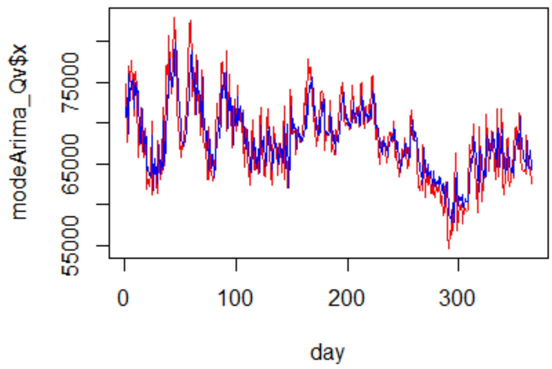


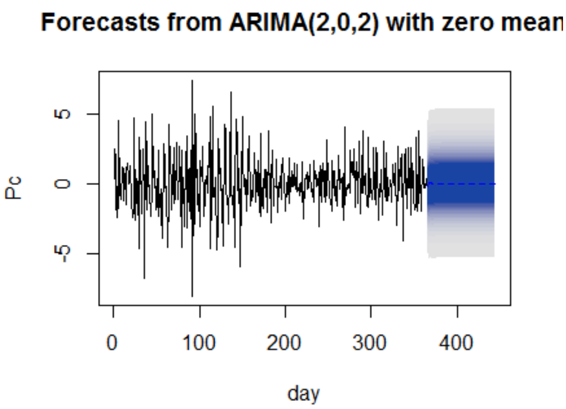

```
data:  Pc
Dickey-Fuller = -2.4757, Lag order = 7, p-value = 0.3762
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.6894, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -2.316, Lag order = 7, p-value = 0.4435
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.8374, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -1.7514, Lag order = 7, p-value = 0.6819
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.0522, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.373, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -7.9599, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

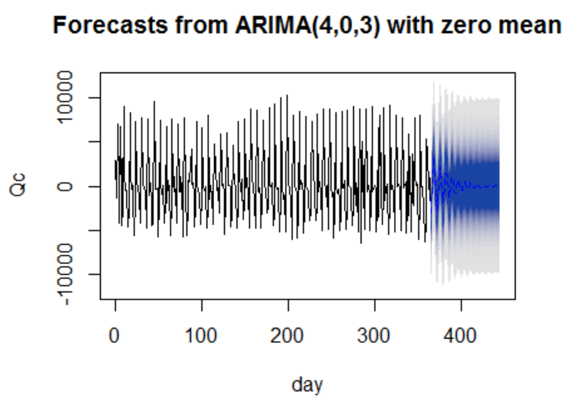

modeArima_Pc$x
day

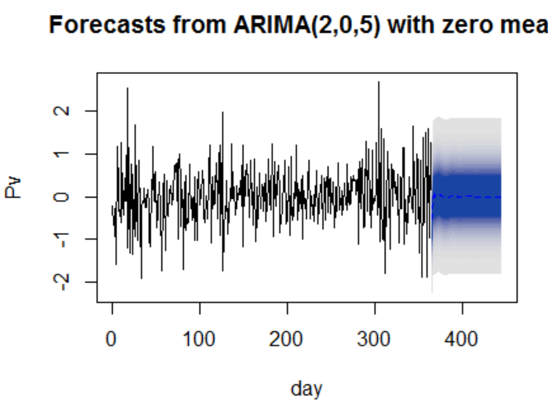

modeArima_Qc$x
day

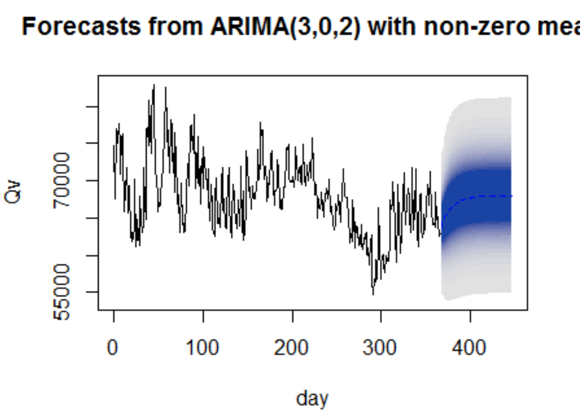

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(2,0,2) with zero mean
Pc
day


Forecasts from ARIMA(4,0,3) with zero mean
Qc
day


Forecasts from ARIMA(2,0,5) with zero mea
Pv
day


Forecasts from ARIMA(3,0,2) with non-zero mea
Qv
day

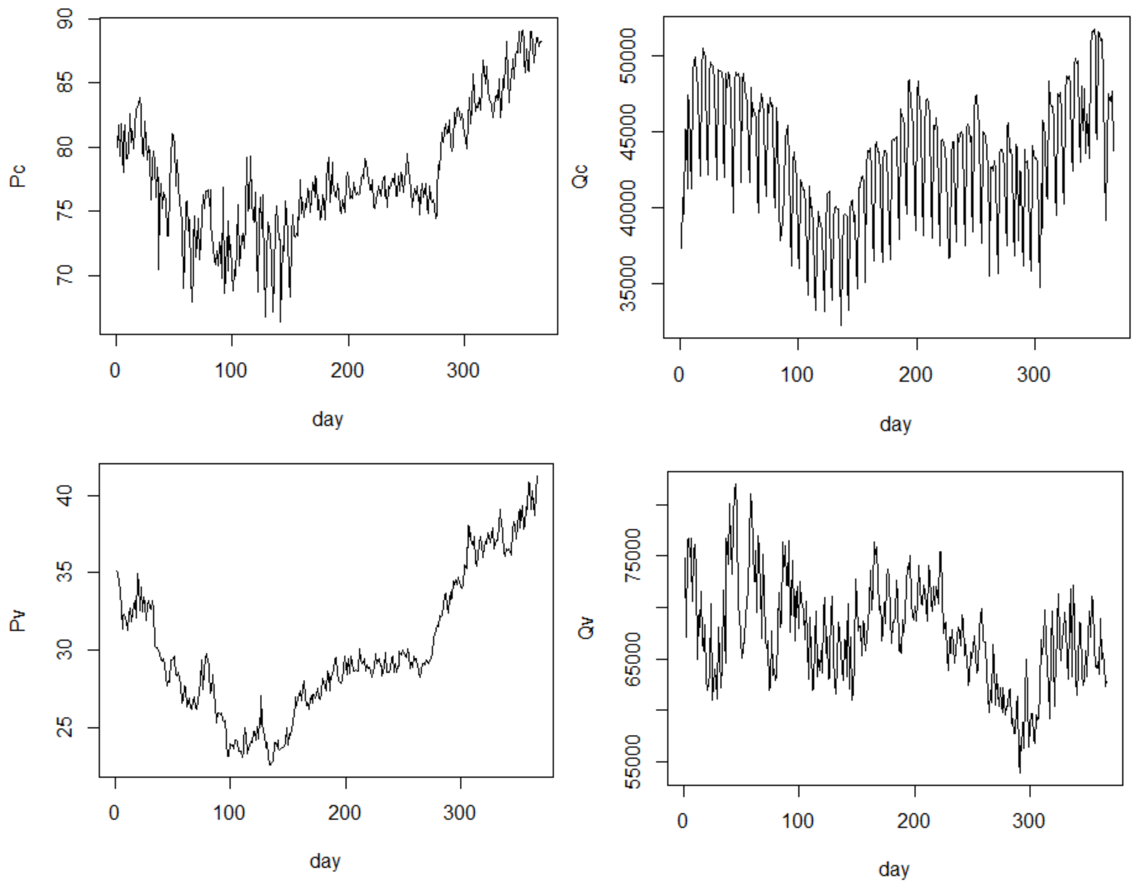
```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
          ar1     ar2     ma1      ma2  intercept
      -0.4296  0.2469  0.0621  -0.6984     0.0222
s.e.   0.0955  0.0868  0.0730   0.0685     0.0300

sigma^2 estimated as 3.4:  log likelihood = -741.54,  aic = 1495.07
```

```
arima(x = diff(Qc), order = c(4, 0, 3))

Coefficients:
         ar1     ar2      ar3      ar4      ma1      ma2     ma3  intercept
      0.1204  0.0054  -0.4845  -0.3617  -0.5900  -0.4576  0.6615    14.8484
s.e.  0.0656  0.0675   0.0586   0.0613   0.0576   0.0784  0.0467    50.2167

sigma^2 estimated as 7196570:  log likelihood = -3401.15,  aic = 6820.3
```

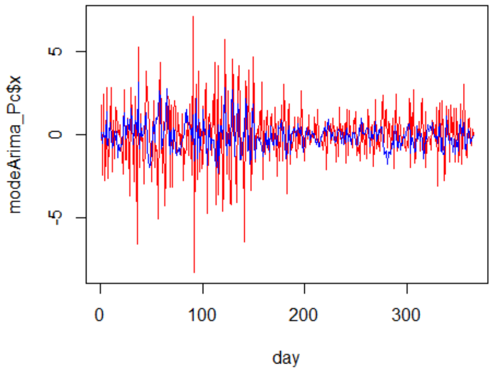
```
arima(x = diff(Pv), order = c(2, 0, 5))

Coefficients:
         ar1     ar2      ma1      ma2     ma3     ma4      ma5  intercept
      0.1386  0.8494  -0.3922  -0.9172  0.2966  0.0749  -0.0374     0.0068
s.e.  0.2517  0.2501   0.2584   0.3195  0.0771  0.0817   0.0571     0.0585

sigma^2 estimated as 0.4525:  log likelihood = -373.39,  aic = 764.78
```

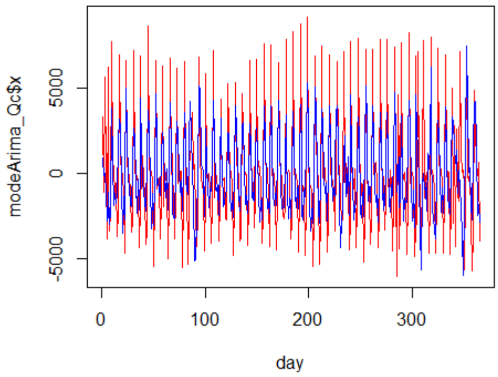
```
arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2     ar3     ma1      ma2  intercept
      0.4955  0.3611  0.0306  0.2009  -0.3471  67977.146
s.e.  0.1644  0.1555  0.1300  0.1573   0.1460   1150.353

sigma^2 estimated as 8958537:  log likelihood = -3449.44,  aic = 6912.88
```

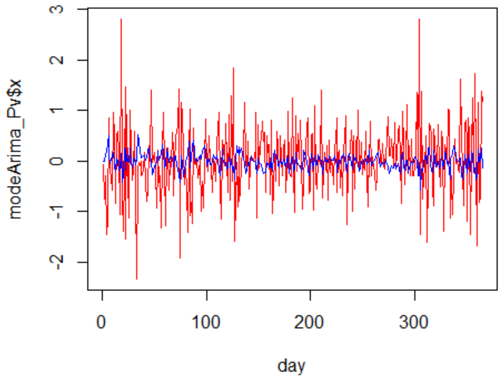
H20 → (7:00pm-7:59pm)

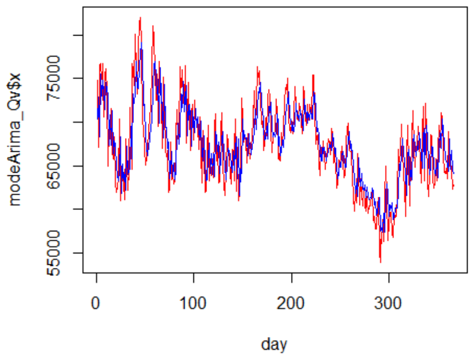


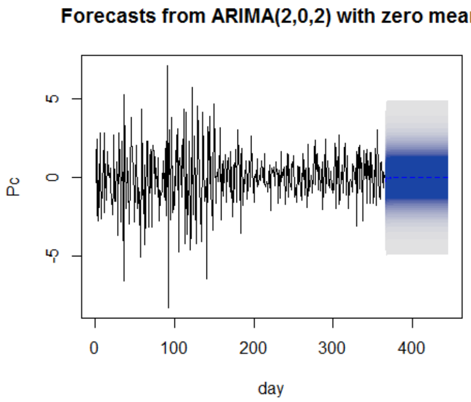

```
data:  Pc
Dickey-Fuller = -2.2058, Lag order = 7, p-value = 0.4901
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.2082, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -1.9171, Lag order = 7, p-value = 0.612
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.6359, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.4342, Lag order = 7, p-value = 0.8157
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -7.7939, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.2296, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  diff(Qv)
Dickey-Fuller = -8.0039, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

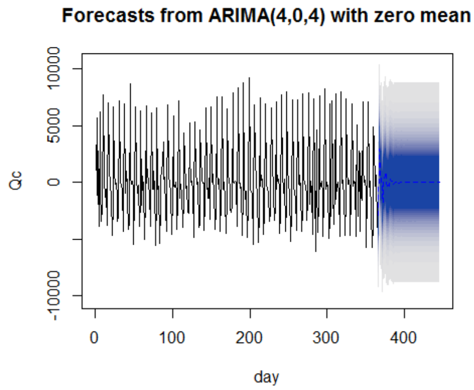

modeArima_Pc$x
day

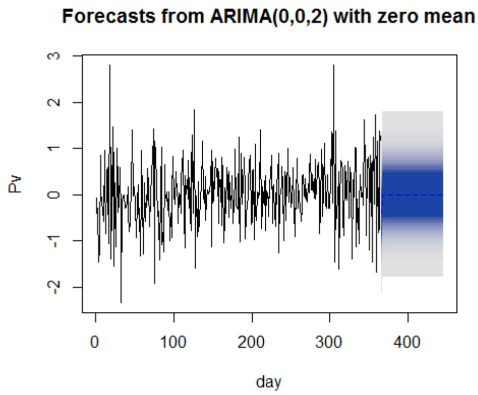

modeArima_Qc$x
day

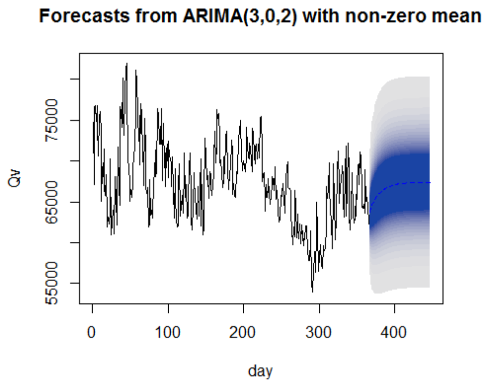

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(2,0,2) with zero mean
Pc
day

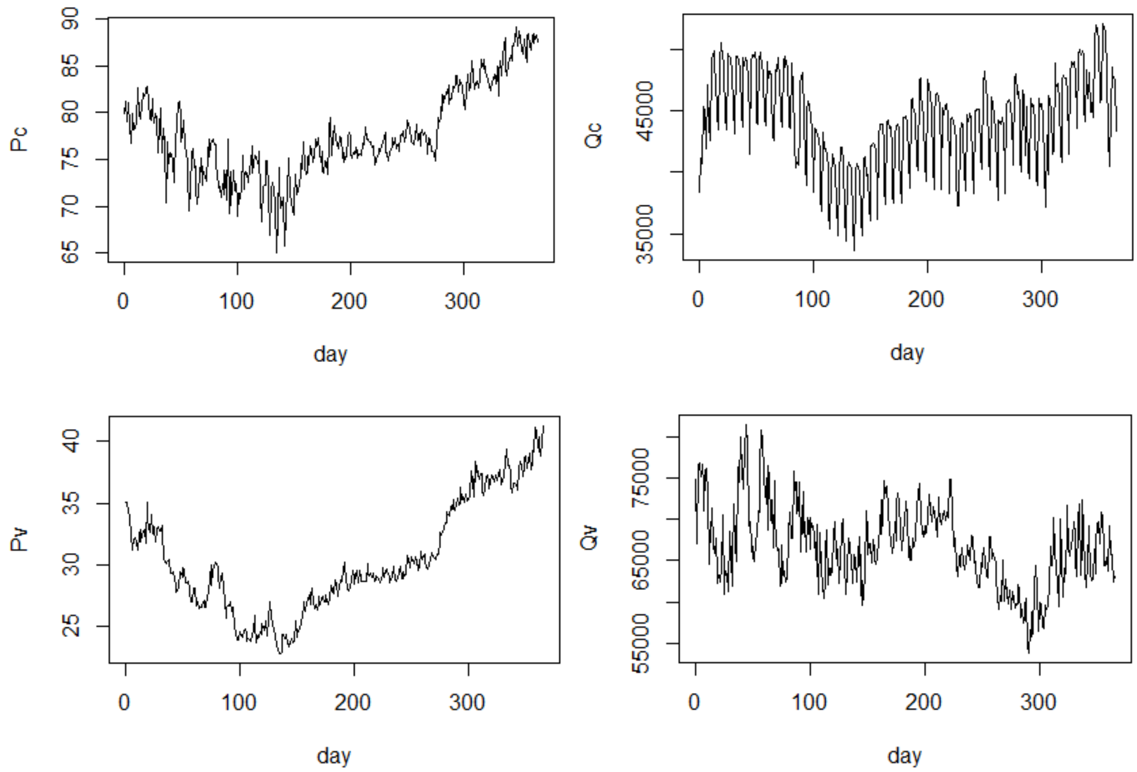

Forecasts from ARIMA(4,0,4) with zero mean
Qc
day


Forecasts from ARIMA(0,0,2) with zero mean
Pv
day

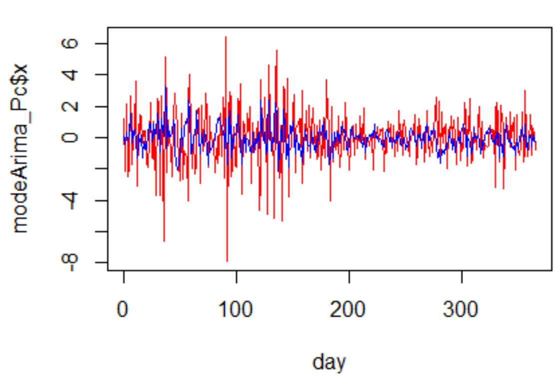

Forecasts from ARIMA(3,0,2) with non-zero mean
Qv
day

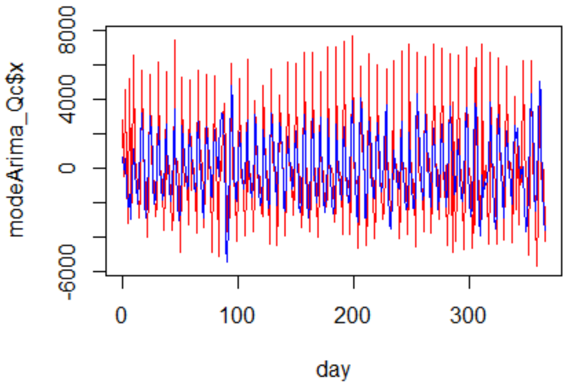
```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
          ar1     ar2    ma1      ma2  intercept
      -0.3489  0.1860  0.021  -0.6253     0.0220
s.e.   0.1266  0.1092  0.109   0.1046     0.0308

sigma^2 estimated as 2.945:  log likelihood = -715.28,  aic = 1442.55



arima(x = diff(Qc), order = c(4, 0, 4))

Coefficients:
         ar1      ar2     ar3      ar4      ma1      ma2      ma3     ma4
intercept
      0.0666  -0.3246  0.0366  -0.5176  -0.3576  -0.2148  -0.4179  0.7524
17.1385
s.e.  0.0839   0.0944  0.0852   0.0683   0.0665   0.0838   0.0590  0.0418
56.4762

sigma^2 estimated as 6051928:  log likelihood = -3369.46,  aic = 6758.93



arima(x = diff(Pv), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.1996  -0.1194     0.0162
s.e.   0.0529   0.0523     0.0242

sigma^2 estimated as 0.4588:  log likelihood = -375.77,  aic = 759.55



arima(x = Qv, order = c(3, 0, 2))

Coefficients:
         ar1     ar2     ar3     ma1      ma2  intercept
      0.5519  0.3264  0.0210  0.1211  -0.3361  67399.069
s.e.  0.1751  0.2049  0.1347  0.1680   0.1544   1170.345

sigma^2 estimated as 8766969:  log likelihood = -3445.47,  aic = 6904.94
```

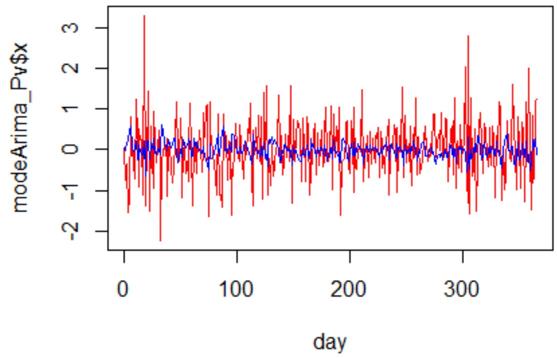
H21 → (8:00pm-8:59pm)

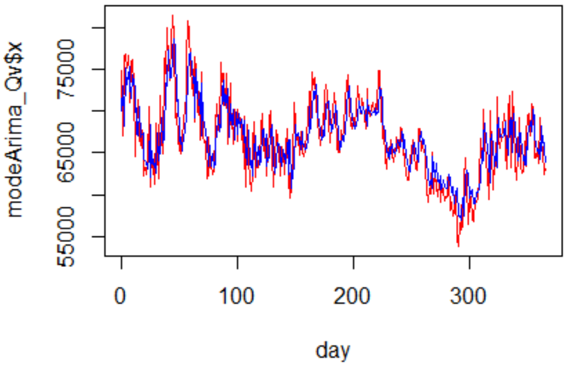


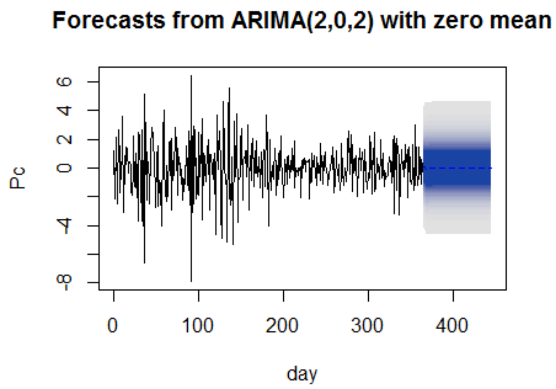

```
data:  Pc
Dickey-Fuller = -2.1324, Lag order = 7, p-value = 0.5211
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.4096, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -1.9833, Lag order = 7, p-value = 0.584
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.4462, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -1.462, Lag order = 7, p-value = 0.804
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -7.9633, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.2276, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.0988, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

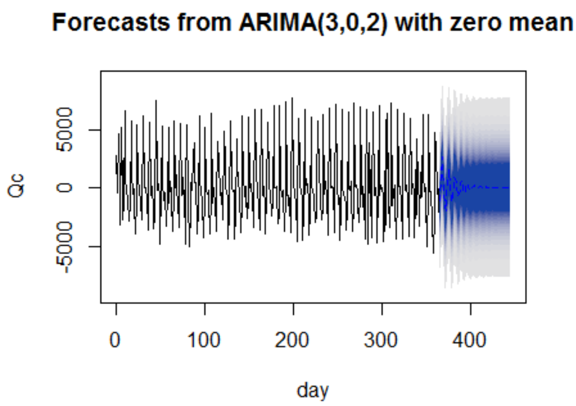

modeArima_Pc$x
day

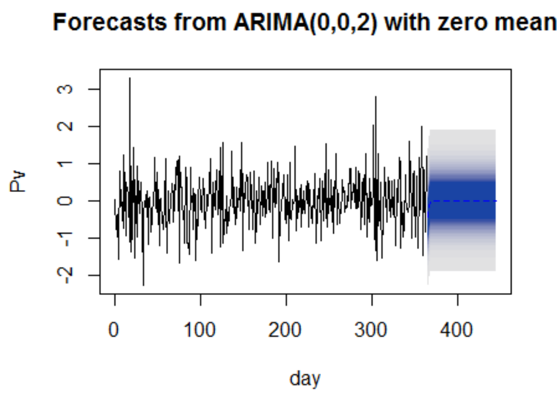

modeArima_Qc$x
day

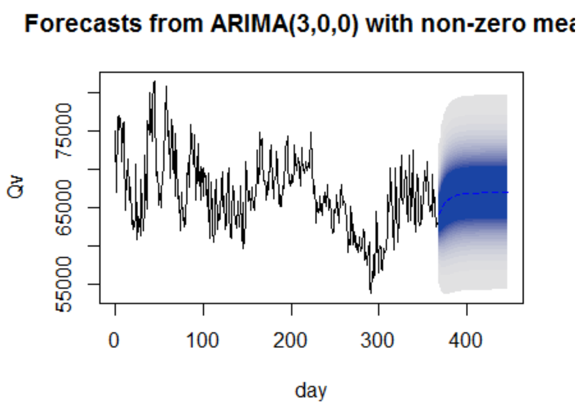

modeArima_Pv$x
day


modeArima_Qv$x
day


Forecasts from ARIMA(2,0,2) with zero mean
Pc
day


Forecasts from ARIMA(3,0,2) with zero mean
Qc
day


Forecasts from ARIMA(0,0,2) with zero mean
Pv
day


Forecasts from ARIMA(3,0,0) with non-zero mea
Qv
day

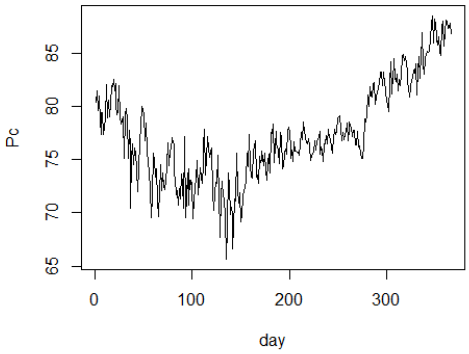
```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
          ar1     ar2     ma1      ma2  intercept
      -0.4319  0.2083  0.0828  -0.6375     0.0223
s.e.   0.1280  0.1151  0.1094   0.1077     0.0310

sigma^2 estimated as 2.606:  log likelihood = -692.93,  aic = 1397.87
```

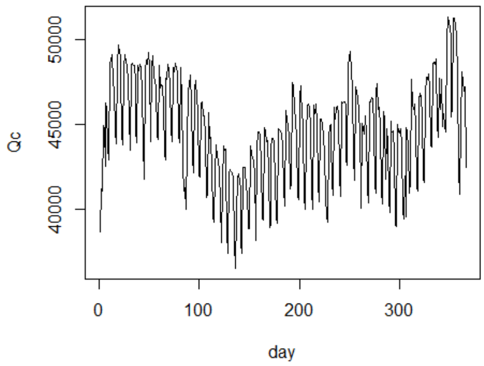
```
arima(x = diff(Qc), order = c(3, 0, 2))

Coefficients:
         ar1      ar2      ar3      ma1     ma2  intercept
      1.0152  -0.6614  -0.1481  -1.4516  0.7539    13.5937
s.e.  0.0680   0.0732   0.0659   0.0492  0.0375    44.6920

sigma^2 estimated as 5011379:  log likelihood = -3334.65,  aic = 6683.29
```

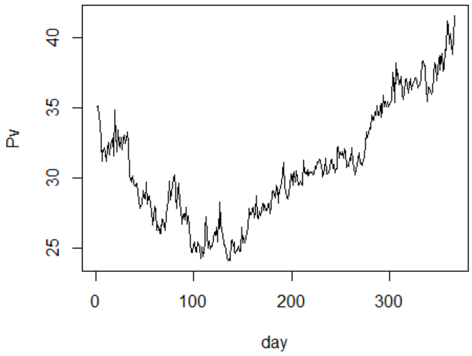
```
arima(x = diff(Pv), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.2440  -0.1033     0.0162
s.e.   0.0532   0.0544     0.0241

sigma^2 estimated as 0.4977:  log likelihood = -390.64,  aic = 789.27
```

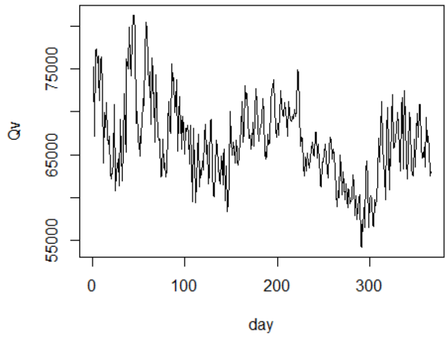
```
arima(x = Qv, order = c(3, 0, 0))

Coefficients:
         ar1      ar2     ar3  intercept
      0.6650  -0.0433  0.2311  66877.649
s.e.  0.0511   0.0628  0.0518   1020.265

sigma^2 estimated as 8631073:  log likelihood = -3442.57,  aic = 6895.15
```

H22 → (9:00pm-9:59pm)

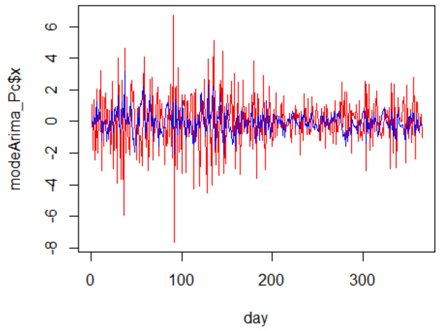


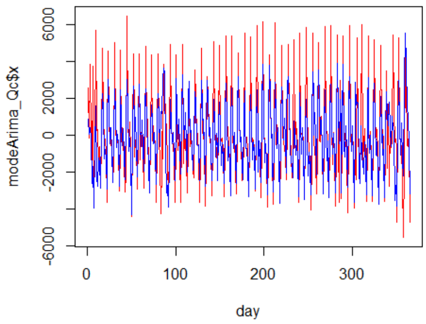


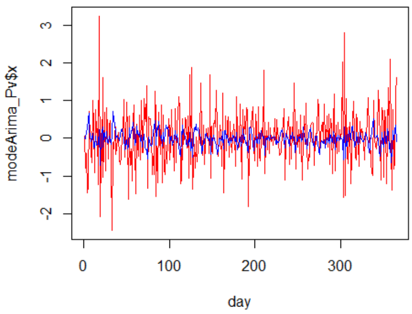


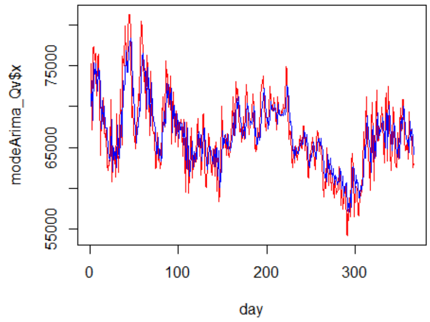



```
data:  Pc
Dickey-Fuller = -2.1678, Lag order = 7, p-value = 0.5061
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -7.9551, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -2.5126, Lag order = 7, p-value = 0.3606
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -7.1748, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.6053, Lag order = 7, p-value = 0.7435
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -8.1986, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.3051, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.1801, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

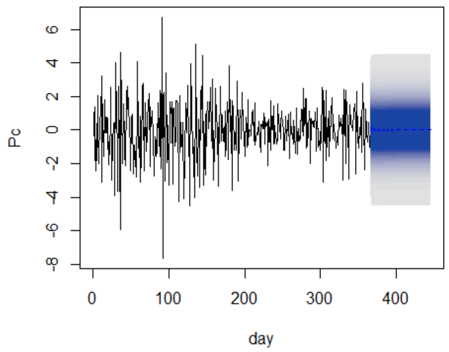




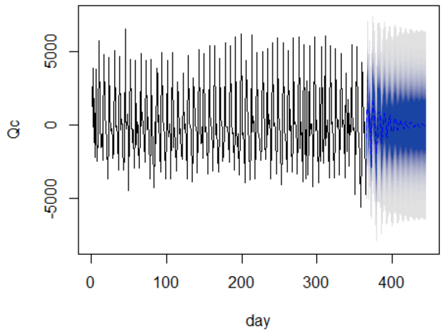




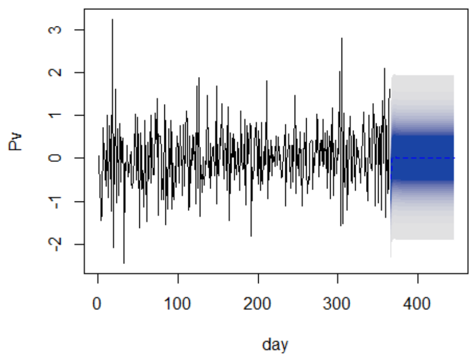
Forecasts from ARIMA(2,0,2) with zero mean



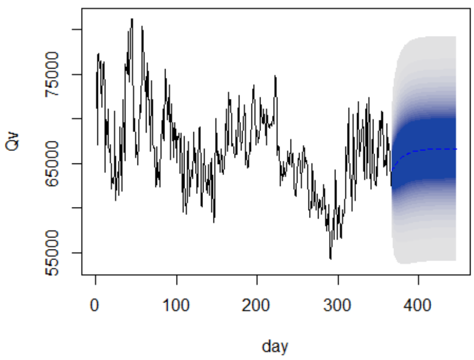
Forecasts from ARIMA(5,0,1) with zero mean



Forecasts from ARIMA(2,0,2) with zero mean



Forecasts from ARIMA(3,0,1) with non-zero mean



```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
          ar1     ar2     ma1      ma2  intercept
      -0.5688  0.3197  0.1830  -0.7448     0.0200
s.e.   0.1025  0.1022  0.0773   0.0789     0.0294

sigma^2 estimated as 2.522:  log likelihood = -687.01,  aic = 1386.03
```

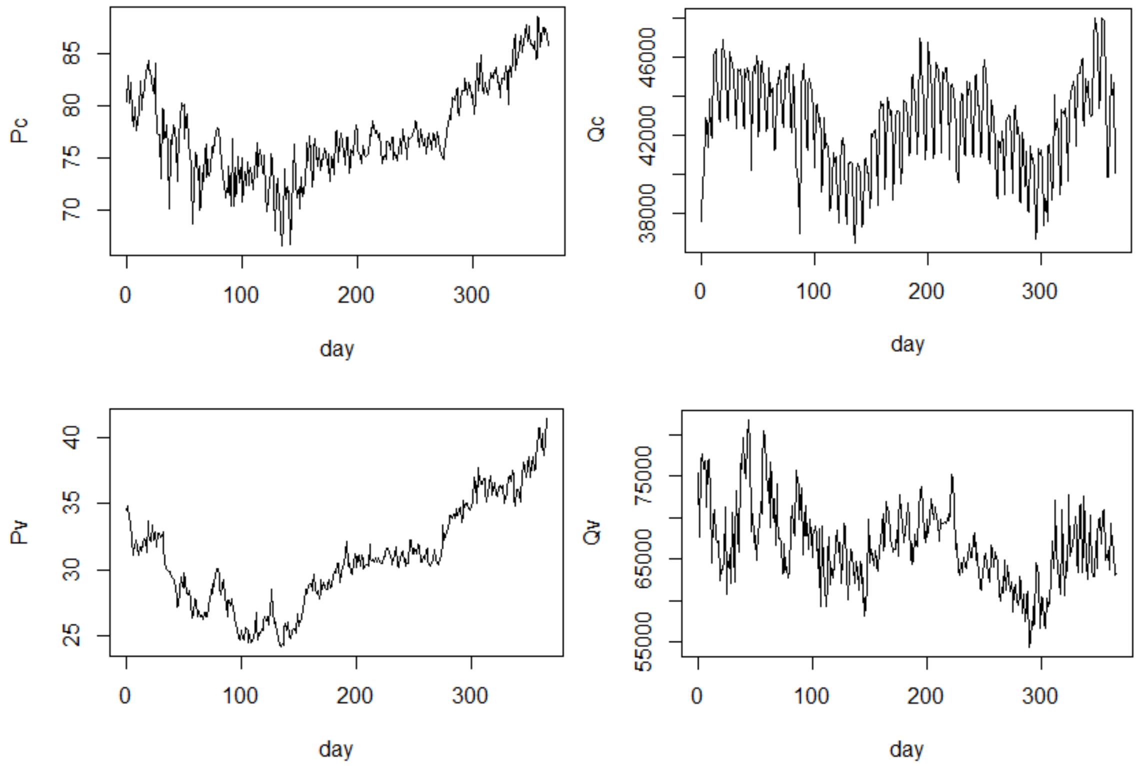

```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
          ar1     ar2     ma1      ma2  intercept
      -0.5688  0.3197  0.1830  -0.7448     0.0200
s.e.   0.1025  0.1022  0.0773   0.0789     0.0294

sigma^2 estimated as 2.522:  log likelihood = -687.01,  aic = 1386.03
```



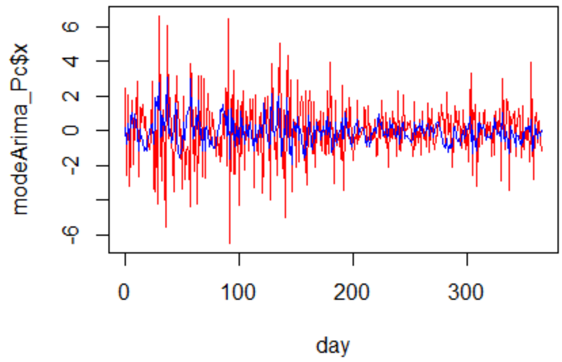
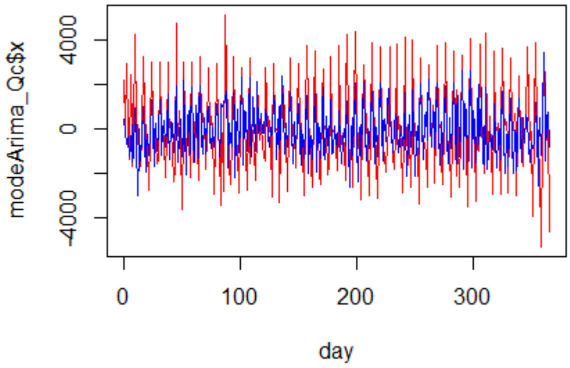
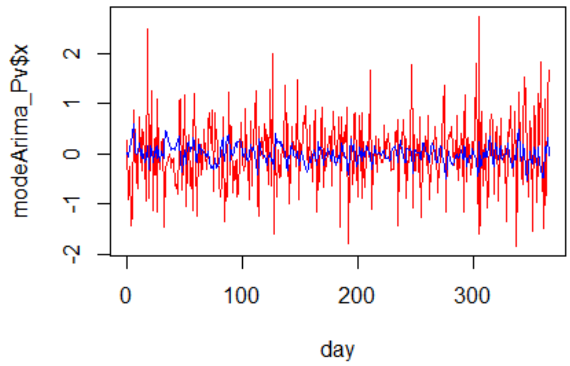
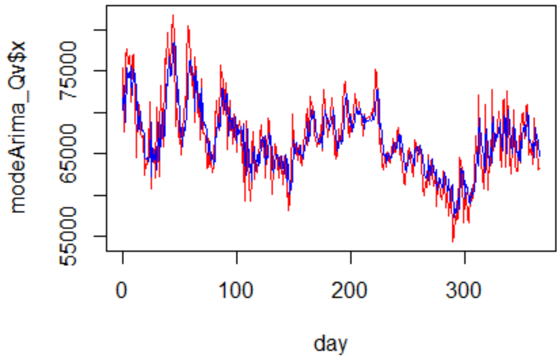
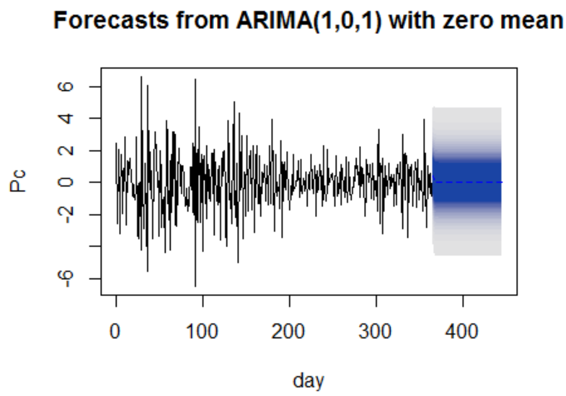
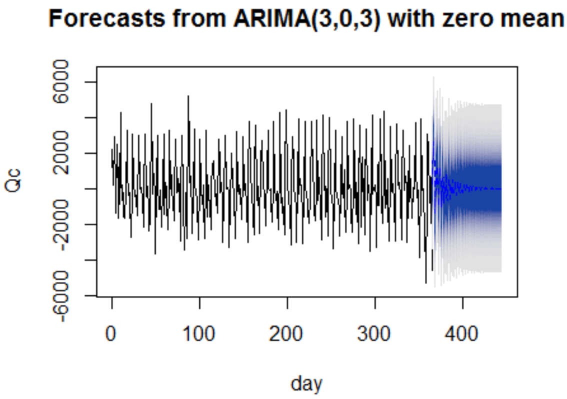
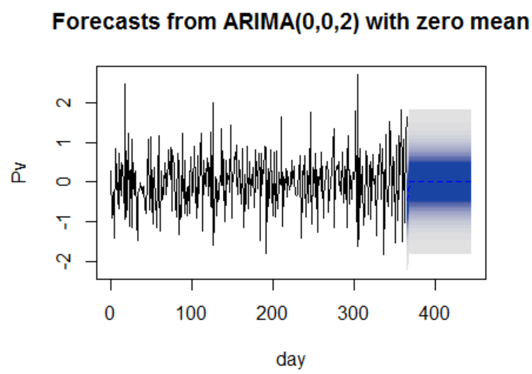
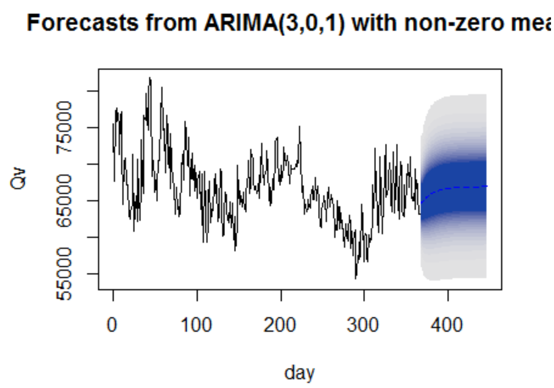
```
arima(x = diff(Pc), order = c(2, 0, 2))

Coefficients:
          ar1     ar2     ma1      ma2  intercept
      -0.5688  0.3197  0.1830  -0.7448     0.0200
s.e.   0.1025  0.1022  0.0773   0.0789     0.0294

sigma^2 estimated as 2.522:  log likelihood = -687.01,  aic = 1386.03
```


```
arima(x = Qv, order = c(3, 0, 1))

Coefficients:
         ar1      ar2     ar3      ma1  intercept
      0.9976  -0.2609  0.1792  -0.3629  66662.012
s.e.  0.1953   0.1361  0.0664   0.1970   1128.838

sigma^2 estimated as 8593832:  log likelihood = -3441.79,  aic = 6895.57
```

H23 → (10:00pm-10:59pm)




```
data:  Pc
Dickey-Fuller = -2.101, Lag order = 7, p-value = 0.5343
alternative hypothesis: stationary


data:  diff(Pc)
Dickey-Fuller = -8.0261, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qc
Dickey-Fuller = -2.6196, Lag order = 7, p-value = 0.3154
alternative hypothesis: stationary


data:  diff(Qc)
Dickey-Fuller = -6.8813, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Pv
Dickey-Fuller = -1.6099, Lag order = 7, p-value = 0.7416
alternative hypothesis: stationary


data:  diff(Pv)
Dickey-Fuller = -7.7891, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  Qv
Dickey-Fuller = -4.3664, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary


data:  diff(Qv)
Dickey-Fuller = -8.1206, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```


modeArima_Pc$x
day

modeArima_Qc$x
day

modeArima_Pv$x
day

modeArima_Qv$x
day

Forecasts from ARIMA(1,0,1) with zero mean
Pc
day

Forecasts from ARIMA(3,0,3) with zero mean
Qc
day

Forecasts from ARIMA(0,0,2) with zero mean
Pv
day

Qv
day

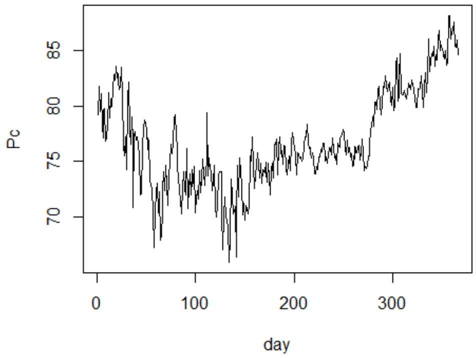
```
arima(x = diff(Pc), order = c(1, 0, 1))

Coefficients:
         ar1      ma1  intercept
      0.4214  -0.8216     0.0168
s.e.  0.0837   0.0550     0.0268

sigma^2 estimated as 2.702:  log likelihood = -699.58,  aic = 1407.16
```

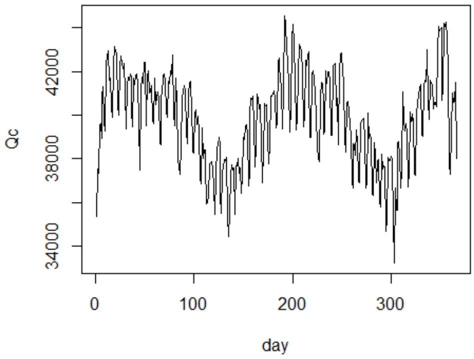
```
arima(x = diff(Qc), order = c(3, 0, 3))

Coefficients:
         ar1      ar2     ar3      ma1     ma2      ma3  intercept
      0.1167  -0.6158  0.5146  -0.1947  0.1838  -0.7628     4.6145
s.e.  0.0803   0.0462  0.0779   0.0778  0.0644   0.0364    17.7065

sigma^2 estimated as 2055229:  log likelihood = -3171.81,  aic = 6359.61
```

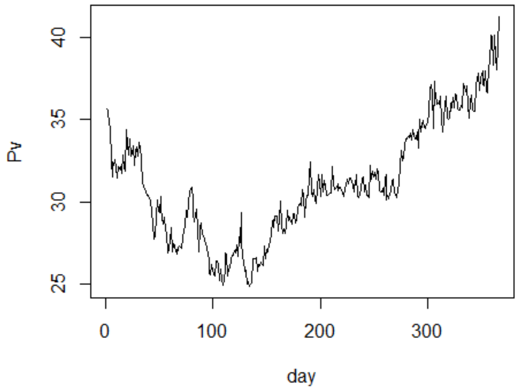
```
arima(x = diff(Pv), order = c(0, 0, 2))

Coefficients:
          ma1      ma2  intercept
      -0.1912  -0.1816     0.0177
s.e.   0.0525   0.0531     0.0226

sigma^2 estimated as 0.4716:  log likelihood = -380.8,  aic = 769.6
```

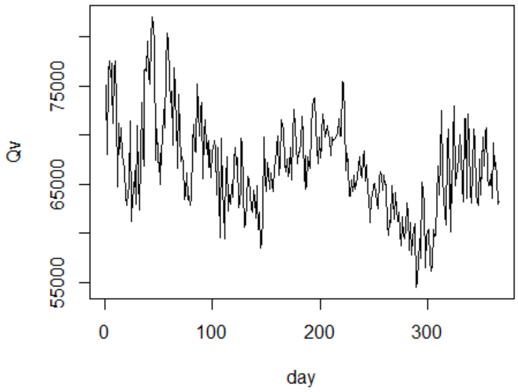
```
arima(x = Qv, order = c(3, 0, 1))

Coefficients:
         ar1      ar2     ar3      ma1  intercept
      1.0320  -0.2888  0.1807  -0.4118  66886.692
s.e.  0.1611   0.1164  0.0636   0.1604   1151.047

sigma^2 estimated as 8618205:  log likelihood = -3442.31,  aic = 6896.61
```

H24 → (11:00pm-11:59pm)

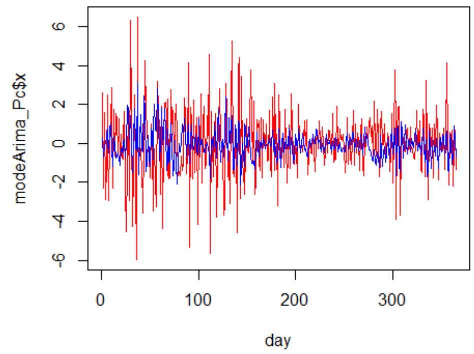


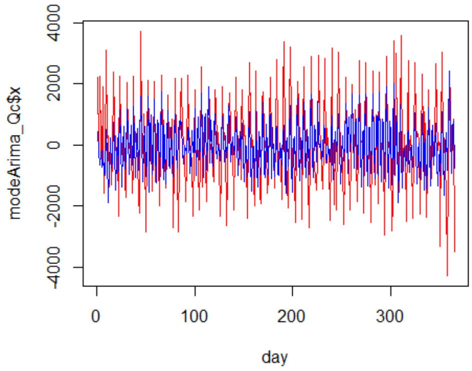


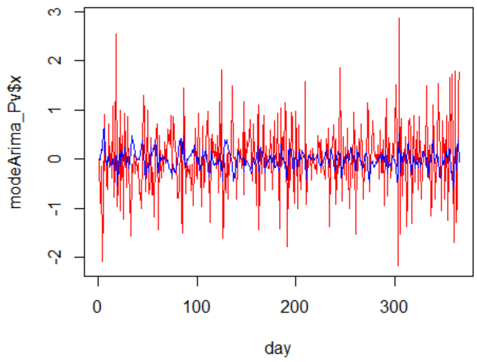


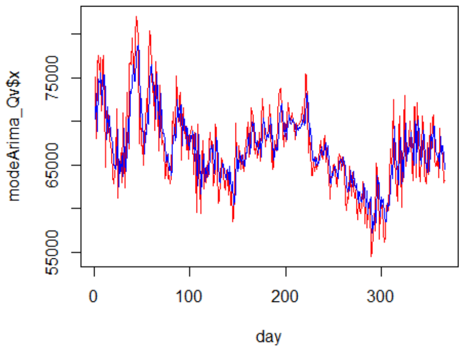



```
data:  Pc
Dickey-Fuller = -2.4153, Lag order = 7, p-value = 0.4017
alternative hypothesis: stationary

data:  diff(Pc)
Dickey-Fuller = -8.105, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qc
Dickey-Fuller = -2.4743, Lag order = 7, p-value = 0.3768
alternative hypothesis: stationary

data:  diff(Qc)
Dickey-Fuller = -6.597, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Pv
Dickey-Fuller = -1.5984, Lag order = 7, p-value = 0.7465
alternative hypothesis: stationary

data:  diff(Pv)
Dickey-Fuller = -7.776, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  Qv
Dickey-Fuller = -4.3385, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

data:  diff(Qv)
Dickey-Fuller = -8.2559, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
```

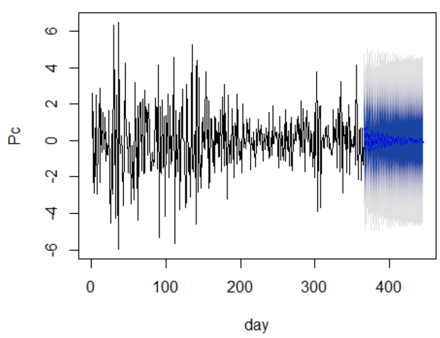




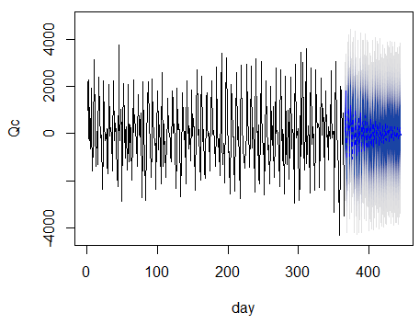




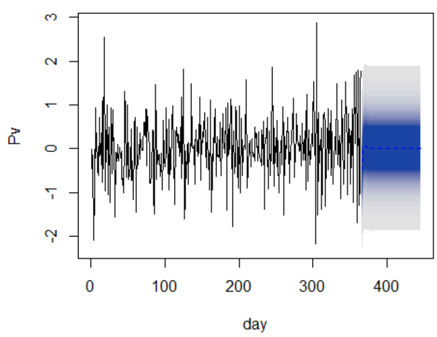
Forecasts from ARIMA(3,0,3) with zero mean



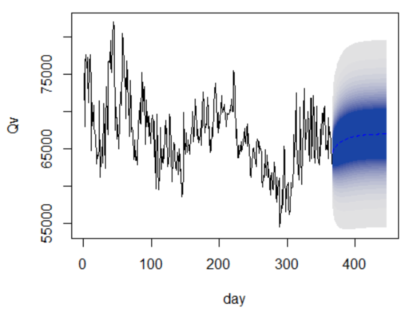
Forecasts from ARIMA(3,0,3) with zero mean



Forecasts from ARIMA(2,0,2) with zero mean



Forecasts from ARIMA(1,0,2) with non-zero mean



```
arima(x = diff(Pc), order = c(3, 0, 3))

Coefficients:
         ar1      ar2     ar3      ma1     ma2      ma3  intercept
      0.1685  -0.6817  0.5789  -0.4762  0.5286  -0.7482     0.0172
s.e.  0.0996   0.0561  0.0789   0.0893  0.0627   0.0638     0.0274

sigma^2 estimated as 2.514:  log likelihood = -686.6,  aic = 1389.2


arima(x = diff(Qc), order = c(3, 0, 3))

Coefficients:
         ar1      ar2     ar3      ma1     ma2     ma3  intercept
      0.2005  -0.6629  0.6248  -0.3108  0.3613  -0.795     4.7673
s.e.  0.0640   0.0335  0.0658   0.0513  0.0604   0.046    18.4174

sigma^2 estimated as 1277366:  log likelihood = -3085.1,  aic = 6186.2

arima(x = diff(Pv), order = c(2, 0, 2))

Coefficients:
         ar1      ar2      ma1     ma2  intercept
      1.1999  -0.4187  -1.4388  0.5929     0.0136
s.e.  0.4157   0.2180   0.4022  0.2794     0.0258

sigma^2 estimated as 0.4909:  log likelihood = -388.14,  aic = 788.27

arima(x = Qv, order = c(1, 0, 2))

Coefficients:
         ar1      ma1      ma2  intercept
      0.9461  -0.3080  -0.2231  67002.934
s.e.  0.0228   0.0578   0.0573   1270.519

sigma^2 estimated as 8465992:  log likelihood = -3439.06,  aic = 6888.11
```

Code with R

#Load following packets

```
library(tseries)
library(stats)
library(forecast)
library(MASS)
library(dynlm)
library(AER)
library(urca)
require(graphics)
```

#Load database

```
data1 <- read.csv("C:/Users/Usuari/Desktop/Datos_definitivos/H22.csv",header=T,dec=",",sep=";")
attach(data1)
str(data1)
```

#Plotting series

```
plot.ts(Pc, xlab="day")
plot.ts(Qc, xlab="day")
plot.ts(Pv, xlab="day")
plot.ts(Qv, xlab="day")
```

#Stationary verification tests

```
adf.test(Pc, alternative='stationary')
adf.test(diff(Pc), alternative='stationary')
adf.test(Qc, alternative='stationary')
adf.test(diff(Qc), alternative='stationary')
adf.test(Pv, alternative='stationary')
adf.test(diff(Pv), alternative='stationary')
adf.test(Qv, alternative='stationary')
adf.test(diff(Qv), alternative='stationary')
```

#Estimation of series

```
modeArima_Pc <- auto.arima(diff(Pc), d=NA,D=NA, max.p = 10, max.q = 10, max.P = 10, max.Q =10,max.order =10, max.d = 10, max.D = 10,start.p = 2, start.q = 2, start.P = 1, start.Q = 1, stationary = TRUE, seasonal = TRUE, ic =c("aicc","aic","bic"), stepwise = TRUE, trace = TRUE, truncate = NULL, xreg = NULL, test=c("kpss","adf","pp"), seasonal.test = c("ocsb","ch"),allowdrift = TRUE,allowmean = TRUE, lambda = NULL, biasadj = FALSE,parallel = FALSE)
plot(modeArima_Pc$x,col="red", xlab="day")
lines(fitted(modeArima_Pc),col="blue")

modeArima_Qc <- auto.arima(diff(Qc), d=NA,D=NA, max.p = 5, max.q = 5, max.P = 2, max.Q =2,max.order =5, max.d = 2, max.D = 1,start.p = 2, start.q = 2, start.P = 1, start.Q = 1, stationary = TRUE, seasonal = TRUE, ic =c("aicc","aic","bic"), stepwise = TRUE, trace = TRUE, truncate = NULL, xreg = NULL, test=c("kpss","adf","pp"), seasonal.test = c("ocsb","ch"),allowdrift = TRUE,allowmean = TRUE, lambda = NULL, biasadj = FALSE,parallel = FALSE)
plot(modeArima_Qc$x,col="red", xlab="day")
lines(fitted(modeArima_Qc),col="blue")

modeArima_Pv <- auto.arima(diff(Pv), d=NA,D=NA, max.p = 30, max.q = 30, max.P = 30, max.Q =30,max.order =30, max.d = 30, max.D = 30,start.p = 2, start.q = 2, start.P = 1, start.Q = 1, stationary = TRUE, seasonal = TRUE, ic =c("aicc","aic","bic"), stepwise = TRUE, trace = TRUE, truncate = NULL, xreg = NULL, test=c("kpss","adf","pp"), seasonal.test = c("ocsb","ch"),allowdrift = TRUE,allowmean = TRUE, lambda = NULL, biasadj = FALSE,parallel = FALSE)
plot(modeArima_Pv$x,col="red", xlab="day")
lines(fitted(modeArima_Pv),col="blue")
```

```
modeArima_Qv <- auto.arima(Qv, d=NA,D=NA, max.p = 30, max.q = 30, max.P = 30, max.Q =30,max.order =30, max.d = 30, max.D = 30,start.p = 2, start.q = 2, start.P = 1, start.Q = 1, stationary = TRUE, seasonal = TRUE, ic =c("aicc","aic","bic"), stepwise = TRUE, trace = TRUE, truncate = NULL, xreg = NULL, test=c("kpss","adf","pp"), seasonal.test = c("ocsb","ch"),allowdrift = TRUE,allowmean = TRUE, lambda = NULL, biasadj = FALSE,parallel = FALSE)
plot(modeArima_Qv$x,col="red", xlab="day")
lines(fitted(modeArima_Qv),col="blue")
```

#Series for forecast

```
Pc_previsto <- forecast.Arima(modeArima_Pc,h = 80, level =c(90,95), fan = FALSE, xreg= NULL, lambda = modeArima_Pc$lambda,bootstrap = FALSE, npaths = 5000, biasadj = FALSE)
plot.forecast(Pc_previsto,plot.conf = TRUE,shaded=TRUE,shadebars = length(Pc_previsto$mean)<5, shadecols = NULL, col=1, fcol = 4,pi.col=1, pi.lty = 2,ylim = NULL, main = NULL, xlab = "day",ylab = "Pc",flty = 2,flwd = 1)
View(Pc_previsto)

Qc_previsto <- forecast.Arima(modeArima_Qc,h = 80, level =c(90,95), fan = FALSE, xreg= NULL, lambda = modeArima_Qc$lambda,bootstrap = FALSE, npaths = 5000, biasadj = FALSE)
plot.forecast(Qc_previsto,plot.conf = TRUE,shaded=TRUE,shadebars = length(Qc_previsto$mean)<5, shadecols = NULL, col=1, fcol = 4,pi.col=1, pi.lty = 2,ylim = NULL, main = NULL, xlab = "day",ylab = "Qc",flty = 2,flwd = 1)
View(Qc_previsto)

Pv_previsto <- forecast.Arima(modeArima_Pv,h = 80, level =c(90,95), fan = FALSE, xreg= NULL, lambda = modeArima_Pv$lambda,bootstrap = FALSE, npaths = 5000, biasadj = FALSE)
plot.forecast(Pv_previsto,plot.conf = TRUE,shaded=TRUE,shadebars = length(Pv_previsto$mean)<5, shadecols = NULL, col=1, fcol = 4,pi.col=1, pi.lty = 2,ylim = NULL, main = NULL, xlab = "day",ylab = "Pv",flty = 2,flwd = 1)
View(Pv_previsto)

Qv_previsto <- forecast.Arima(modeArima_Qv,h = 80, level =c(90,95), fan = FALSE, xreg= NULL, lambda = modeArima_Qv$lambda,bootstrap = FALSE, npaths = 5000, biasadj = FALSE)
plot.forecast(Qv_previsto,plot.conf = TRUE,shaded=TRUE,shadebars = length(Qv_previsto$mean)<5, shadecols = NULL, col=1, fcol = 4,pi.col=1, pi.lty = 2,ylim = NULL, main = NULL, xlab = "day",ylab = "Qv",flty = 2,flwd = 1)
View(Qv_previsto)
```

#Model equations

```
summary(modeArima_Pc)
summary(modeArima_Qc)
summary(modeArima_Pv)
summary(modeArima_Qv)
```